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“Smart Shopping”:

Implications of Hard-Discounters

and Multiple-Store Patronage

Mark Vroegrijk

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Proefschrift

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CONTENTS

Chapter 1 Introduction

The recent economic downturn has made today's grocery shoppers more price-conscious – and increasingly focused on keeping their expenditures in check (AdNews 2011; Nielsen 2011; Verdict Research 2009). Accordingly, consumers have altered their shopping behavior as well, aligning it to this enhanced emphasis on savings. Two interesting examples of such "smart shopping" behavior are the increased popularity of the so-called "hard-discounter" store format, as well as a rise in systematic multiple-store patronage (EFMI and CBL 2010; Gijsbrechts, Campo and Nisol 2008; Steenkamp and Kumar 2009). While these two developments both play an important role in shaping consumers' grocery shopping behavior (often even going hand in hand), they have remained relatively unexplored in the academic literature so far. This dissertation aims to bridge this gap, and specifically investigates the hard-discounter and multiple-store shopping phenomena in terms of (i) their interrelationship, (ii) their implications for consumers' purchase and/or spending behavior, and (iii) their impact on "traditional" retailers' market performance (and how it could be responded to). A short overview of both phenomena is provided in the paragraphs below.

The hard-discounter format originated in Germany, pioneered by Aldi and at a later stage successfully adopted by other chains like Lidl. Its business model strongly focuses on cutting costs, which is realized through a limited assortment (between 1000 – 1500 SKUs on average) that primarily comprises private label products (about 90%), and makes for efficient operations. In addition, hard-discounter outlets are basic and functional in terms of layout, and staffing levels are kept to a minimum (Steenkamp and Kumar 2009). Together, this allows hard-discounters to offer extremely low prices – lying between 40 to 60% below those of national brands sold at more traditional chains (Nielsen 2007; Nauwelaers, Renders and

Vandenbroucke 2012). This large price advantage, together with the fact that the format has become more socially accepted and geographically accessible to consumers (Costa et al. 2006; Steenkamp and Kumar 2009) has made hard-discounters one of the most important players in the grocery business. Despite this importance, however, the format has remained largely understudied, with prior research mainly focusing on another and vastly different type of discounter: the “large-discounter” (i.c. Wal-Mart, Ailawadi et al. 2010; Gielens et al. 2008; Singh, Hansen and Blattberg 2006). Studies that do consider hard-discounters, have primarily aimed to uncover the key success factors behind the format (e.g. Colla 2003; Gerhard and Hahn 2005). To our knowledge, a paper by Cleeren et al. (2010) is the only study that assesses the competitive impact of hard-discounters on traditional retailers’ performance. While the aforementioned study provides interesting insights regarding the magnitude of this impact, it does not explicitly address what the underlying antecedents are – nor does it reflect on how traditional retailers may mitigate this impact. This dissertation will therefore aim to cover these topics.

As stated above, the second development of interest for this dissertation is the rise of (systematic) multiple-store patronage. Instead of buying all groceries at a single store, consumers may visit two or more grocery stores on a regular basis – and allocate their purchases between them (Gijsbrechts et al. 2008). This form of shopping behavior has become increasingly common over the years, and has now been adopted by a majority of grocery shoppers (EFMI and CBL 2010; Fox 2005; Gijsbrechts et al. 2008). Previous studies have identified various drivers of multiple-store shopping behavior, including variation in stores’ (product) offer, trip type-dependent store preferences, and – in line with the starting point of this dissertation – the savings potential that arises from price differences between stores (Cude and Morganosky 2001; Fox and Hoch 2005; Gijsbrechts et al. 2008; Krider and Weinberg 2000). While the antecedents of multiple-store shopping have thus received quite some attention in the current marketing literature, much less is known about the consequences of this behavior – both from the retailer's and the consumer's perspective. For one, little is known about how multiple-store shopping affects retailers' vulnerability to other market players and/or entrants. For another, it remains unclear how this alternative way of shopping affects in-store decision making, i.e. what and how much consumers actually choose to buy in the stores. However, given that multiple-store patronage has become the rule rather than the exception among grocery shoppers, such insights are increasingly relevant. The current dissertation will therefore aim to shed more light on these issues as well.

In the next two paragraphs of this chapter (§1.1 and §1.2), a more extensive overview will be given on the subjects of hard-discounters and multiple-store shopping. A review of related studies is provided, along with an indication of the most salient gaps that still exist in the literature. Accordingly, the focal research topics of the dissertation will be covered, along with a discussion on how they contribute to bridging the aforementioned literature gaps. §1.3 then provides an outline of the remaining chapters in the dissertation.

1.1 The Hard-Discounter Format

Hard-discounters have become an increasingly common sight in today's retailing landscape. While the format originated in Germany, the two main hard-discounter chains Aldi and Lidl are nowadays both ranked among the top 25 retailers worldwide, and can be found in over twenty European countries (Nielsen 2007; Retail Forward 2004). Their expansion has proceeded at an especially rapid pace during the last two decades, as is evident from the number of European discounter outlets nearly doubling between 1991 and 2005 (Costa et al. 2006). Moreover, the format is steadily making its way to Eastern Europe, Australia, Canada and the US as well (Retail Forward 2004). As a result of this growing presence, hard-discounters have become more and more accessible to consumers – a Dutch survey, for example, indicating that the vast majority (80%) of consumers has a hard-discounter outlet available in their near vicinity (EFMI and CBL 2010).

Along with this improvement in accessibility, goes an increased acceptance of the format among shoppers. Due to accumulated consumer experience over the years, hard-discounters have gained considerable trust, and no longer solely target the poor (Costa et al. 2006; Steenkamp and Kumar 2009). This, along with their price leadership over their competitors (as is recognized by a majority of consumers; OIVO 2010) has made the hard-discounter format a considerable force within grocery retailing. This is illustrated by the percentage of shoppers that buy products at a hard-discounter, which amounts to 70% in countries like Belgium and the Netherlands, and even over 80% in Germany (EFMI and CBL 2010; Nielsen 2007; OIVO 2010). Accordingly, the format is found to capture up to 30-40% of grocery sales in some countries (Cleeren et al. 2010; Hansen and Kliger 2004).

Prior research on the hard-discounter format is mostly descriptive in nature, and has primarily aimed to identify the key drivers of its success (e.g. Colla 2003; Gerhard and Hahn 2005). Next to the factors discussed above, these studies conclude that the main strength of hard-discounters does not solely lie in their rock-bottom prices, but also in the fact that these low prices go hand in hand with excellent product quality. Hard-discounters often contract renowned national brand manufacturers to produce their private labels, and are not afraid to remove items from their assortments when quality is not up to par (Gerhard & Hahn 2005). Moreover, by offering an additional and weekly-changing selection of special items, hard-discounters are able to repeatedly attract steady flows of traffic to the store.

While these studies are certainly valuable in explaining the strong position of hard-discounters in general, they do not yet provide a clear insight into how hard-discounters affect the market performance of competing (traditional) retailers in particular. Only recently, this topic has slowly started to receive attention from academics, with a study by Cleeren et al.

(2010) analyzing how the advent of hard-discounters affects the profitability of traditional retailers. Interestingly, the study concludes that while the local market entry of a hard-discounter has an immediate negative impact on incumbent retailers' market shares, their profitability only starts to deteriorate when more hard-discounters enter the market.

Current literature gaps

The findings by Cleeren et al. (2010) show that the extent to which a hard-discounter affects the performance of traditional retailers, depends on the configuration of the trading zone in which these stores operate. However, other factors may be at play as well. First, some traditional retailers may be more vulnerable to hard-discounters than others. Indeed, some industry sources suggest that it is especially the value-oriented retailer (as compared to "upscale", full-service retailers) who will experience difficulty in withstanding the hard-discounter threat (Fem Business 2006; Foodmagazine 2009). However, such claims are yet to be empirically verified. Second, a retailer's geographical location vis-à-vis the hard-discounter seems to matter as well. Business press has, however, not yet reached a consensus on whether retailers should prefer a location close to, or further away from the hard-discounter (Foodmagazine 2009; Levensmiddelenkrant 2010) – and again, no empirical support is available to resolve this issue.

In all, the impact of hard-discounters on traditional retailers, and its possible antecedents, is not yet fully understood. This limited knowledge on the (drivers of the) impact of hard-discounters on traditional supermarkets, makes it more difficult to theorize on effective response strategies as well. Currently, traditional retailers often respond to hard-discounters in the area where they are at the most obvious disadvantage: price. While the consequences of some of these strategies (e.g. large-scale price cuts; Van Heerde, Gijsbrechts and Pauwels 2008) have been assessed by prior studies, the effectiveness of others, such as the proliferation of a budget private label line or the launch of an own discount subsidiary

(Ailawadi, Pauwels and Steenkamp 2008; Cleeren et al. 2010) has remained largely unexplored. The viability of alternative, non-price-based response strategies is yet to be determined as well.

Contribution of this dissertation

This dissertation aims to bridge some of the gaps discussed above. First, we provide a new perspective on the impact of hard-discounters, by viewing it from a multiple-store shopping perspective. Even though many consumers shop at a hard-discounter, the format is seldom visited in isolation – and even rarely constitutes a consumer’s primary store (e.g. only for 26% of Dutch hard-discounter shoppers; EFMI and CBL 2010). Given this premise, we offer a richer view on how hard-discounters impact traditional retailers, by studying how these formats compete for customers – and more importantly in this context – for their share-of-wallet.

Second, our focus on multiple-store shopping uncovers several antecedents of the impact of hard-discounters. For example, a retailer’s vulnerability to hard-discounters may depend on the extent to which the retailer possesses distinct strengths of its own – and as such can “complement” a hard-discounter (Gijsbrechts et al. 2008). Moreover, as a retailer’s geographical location determines the relative ease of being visited alongside the hard-discounter, this may drive the latter’s impact as well – an issue that we will empirically explore and support in this dissertation. In addition, we will deduct different response strategies from these antecedents, along with a test of their viability.

Third, this dissertation will assess the effectiveness of an increasingly-used response strategy vis-à-vis hard-discounters: the proliferation of an economy private label. While traditional retailers can opt for other (price-based) response strategies as well (such as the launch of an own discount subsidiary), economy private labels are relatively easy to implement and align perfectly with the increasing popularity of “multi-tiered” private label strategies (Geyskens, Gielens and Gijsbrechts 2010). However, as of yet, it remains unclear whether these economy private labels are truly effective in defending against the hard-discounter threat. This question is especially relevant given that some studies (e.g. Hansen and Singh 2008) suggest that they may actually yield the opposite effect – that is, make consumers more (instead of less) prone to switch to a lower-priced competitor. This dissertation will, therefore, empirically assess whether economy private labels can be an appropriate defense tool vis-à-vis hard-discounters – and if so, under what circumstances.

1.2 Multiple-Store Shopping

Today's consumers have a wide range of different (product) needs to fulfill (e.g. for groceries, clothing, electronics, personal entertainment, et cetera) and, to satisfy these needs, they have to patronize different stores. The question on how consumers organize their visits to these stores, frequented for different purposes, has already been covered by several academics (e.g. Dellaert et al. 1998; Popkowski Leszczyc and Timmermans 2001).

However, consumers do not just visit multiple stores because they serve different purposes. A current trend is that even for groceries alone, consumers often visit more than one store – and (systematically) allocate their purchases between them. Such "single-purpose, multiple-store shopping" behavior is nowadays adopted by a majority of grocery shoppers, with reported figures ranging from 60 to over 80% of consumers (EFMI and CBL 2010; Fox 2005; Gijsbrechts et al. 2008; Stassen, Mittelstaedt and Mittelstaedt 1999). This rise in multiple-store patronage is fuelled by several recent developments. First, the retailing landscape has become increasingly diverse; grocery stores can now operate under a multitude of vastly different formats, making their (product) offers more unique and less interchangeable (Morganosky 1997). Second, for many trading areas, the number of available grocery outlets has greatly expanded over the years – allowing consumers easy access to multiple grocery chains. This is illustrated by a recent Dutch survey, which indicates that on average, consumers have more than four different grocery chains located in their near vicinity (EFMI and CBL 2010). Finally, consumers have become more mobile themselves, making it easier for them to visit more than one store on a frequent basis – even if the stores are somewhat remotely located.

Still, the prevalence of multiple-store (grocery) shopping cannot be ascribed to changing market circumstances alone. To begin with, consumers may prefer different stores for different categories (e.g. because the stores vary in their positioning and/or the availability of specific items), and therefore choose not to limit themselves to just one store (Cude and Morganosky 2001; Gijsbrechts et al. 2008). In addition, since shopping objectives can differ on a trip-by-trip basis, consumers may visit a set of stores that can jointly satisfy these objectives (e.g. a store close by may be preferred for quick “fill-in” trips, while a more distant, but better-stocked (or lower-priced) store is chosen on more extensive “major” trips) (Krider and Weinberg 2000; Gijsbrechts et al. 2008). Perhaps the most common reason for multiple-store shopping, however, is that the patronage of more than one store allows consumers to capitalize on the price differences between these stores – and thus helps them to save money as a result (Fox and Hoch 2005; Mägi and Julander 2005).

Current literature gaps

While the current marketing literature provides valuable insights into the underlying drivers of (multiple-store) shopping patterns, much less is known about how and when consumers switch between these different patterns, and about the implications of such behavior. First, from a competitive point of view, Gijsbrechts et al. (2008) indicate that – depending on whether single- or multiple-store shopping prevails – grocery stores either primarily compete for customers, or for their share-of-wallet, respectively. However, given that some stores (such as hard-discounters; EFMI and CBL 2010) are intrinsically more prone to be part of a multiple-store shopping pattern than others, it has remained unclear what this notion implies for the actual degree of competition between (different types of) grocery stores – and the underlying drivers of these relationships.

Second, from the consumer's perspective, the current literature primarily sheds light on how multiple-store shopping affects consumers' store choice decisions (e.g. Gijsbrechts et al. 2008; Krider and Weinberg 2000). Yet, much less is known about the impact on spending behavior, i.e. whether consumers still spend similar amounts of money when they engage in (different forms of) multiple-store shopping. Given that multiple-store shopping constitutes an entirely different way of grocery shopping (compared to the single-store "standard"), but is at least as popular, this issue has become increasingly relevant to address.

Contribution of this dissertation

Again, this dissertation aims to cover the topics discussed above. First, we study consumers' shopping patterns (including single-store and (different types of) multiple-store shopping) within a dynamic context; that is, both before and after the local entry of a hard-discounter. By tracking consumers' shopping patterns over time, we shed light on how such a major event affects how consumers switch between different patterns – and more specifically, their tendency to engage in multiple-store shopping behavior.

Second, through our comparison of consumers' shopping patterns before and after local hard-discounter entry, we provide insights into the nature of competition between hard-discounters and traditional supermarket chains. Specifically, our analysis allows us to assess the vulnerability of (differently positioned) market players to the hard-discounter format, both in terms of their clientele and their share-of-wallet. Moreover, by relating these losses to chain characteristics – and, given the role of multiple-store shopping, the interactions between them – we are able to identify important drivers of these competitive relationships.

Finally, this dissertation will provide a clearer view on consumer grocery spending and how this varies across different shopping patterns. By tracking consumers' shopping patterns alongside their specific purchase behavior, we can assess consumers' expenditures across the different shopping patterns in which they engage, and more specifically: whether multiple-store shopping and/or the patronage of hard-discounters systematically affect how much consumers spend on their groceries. Such particular insights are especially interesting given that savings are a common reason to engage in such forms of shopping behavior (Costa et al. 2006; Mägi and Julander 2005; Stassen, Mittelstaedt and Mittelstaedt 1999) – but they also add to current knowledge on the relationship between shopping patterns and subsequent decision making (e.g. Kahn and Schmittlein 1989).

1.3 Dissertation Outline

In addition to the current (introductory) chapter, this dissertation comprises three research-based chapters. In these chapters, we investigate the hard-discounter and/or multiple-store shopping phenomena, both in terms of their interrelationship, as well as their implications for (traditional) retailers and consumers. Table 1.1 summarizes the contents of these three chapters, showing that chapter 2 provides a "broader" view on both hard-discounters and multiple-store shopping, while chapters 3 and 4 zoom in on specific sub-topics. Each of the chapters is described in more detail in the paragraphs below.

Chapter 2 ("Close Encounter with the Hard-Discounter: A Multiple-Store Shopping Perspective on the Impact of Local Hard-Discounter Entry") studies how the local entry of a hard-discounter outlet affects consumers' shopping behavior and, consequently, the market performance of incumbent chains. For this purpose, we model households' period-by-period choice of (grocery) shopping patterns, and thereby explicitly account for the advent of multiple-store shopping – a form of grocery shopping that often goes hand in hand with hard-discounter patronage (EFMI and CBL 2010). We underline this (important) role of multiple-store shopping in our conceptual framework, and use it to theorize on the vulnerability of "traditional" retailers to the hard-discounter format, as well as its main underlying drivers. By employing a dataset that covers nearly 200 local hard-discounter entries (and the purchase behavior of more than 700 households), we are not only able to empirically assess these claims, but also to identify and test different response strategies to hard-discounter entry – ranging from "heads-on" price competition to more cooperative approaches.

TABLE 1.1
Overview of Research-Based Chapters

	Topic		**Implications (for retailers)**			**Implications (for consumers)**	
	Hard-discounters	**Multiple-store shopping**	**Nature of competition**	**Drivers of competition**	**Response to competition**	**Purchase behavior**	
Ch. 2	√	√	√	√	√	Store patronage	Share-of-wallet
Ch. 3	√		√		√		Category volume
Ch. 4	√	√					Overall spending

Chapter 3 ("Battling for the Household's Category Buck: Can Economy Private Labels Help Defend Against the Hard-Discounter Threat?") zooms in on the effectiveness of an increasingly-used defense to hard-discounters: the introduction of an "economy" private label. While this cheaper variant of "standard" private labels allows traditional retailers to match or even beat the prices offered at hard-discounters, extant research suggests that it also makes customers more price-conscious – and therefore more (rather than less) susceptible to the hard-discounter format (Corstjens and Lal 2000; Hansen and Singh 2008). To gain a better insight into this matter, we adopt a difference-in-difference modeling approach that helps us quantify retailers' (category) losses from hard-discounter entry, and relate the size of these losses to the absence or presence of an economy private label. Moreover, we provide guidelines on the specific product categories in which retailers are most vulnerable to hard-discounters, and/or where economy private labels are an appropriate defense. We do so by using data on 48 product categories (in which a major Dutch retailer introduced an economy private label), 45 hard-discounter entries, and the grocery purchase behavior of nearly 400 households.

Chapter 4 (“Save or (Over-)Spend? How Shopping Pattern Choice Affects Consumer Grocery Spending”) focuses on the spending implications of different types of (grocery) shopping patterns (including multiple-store shopping and/or the patronage of hard-discounters). Its main point-of-departure lies in a commonly used motive for such shopping patterns: consumers’ desire to cut back on their grocery expenses. Building on insights from the consumer behavior literature (e.g. MacInnis and Jaworski 1989), we propose that shopping patterns not only vary in the savings opportunities that they provide, but also affect consumers’ ability and motivation to save in different ways. This raises the question of how much consumers actually spend across different shopping patterns – and specifically, whether actual expenditures under multiple-store shopping and/or hard-discounter patronage are consistent with consumers’ saving goals. We empirically address this issue by analyzing households’ grocery expenditures across the different shopping patterns they engage in, while controlling for both situational and household-specific factors. Our data covers the shopping and spending behavior of more than 1300 households (across 300+ categories), and yields insights into how consumer spending is shaped by (i) whether one or multiple stores are visited, (ii) the store format(s) chosen, and (iii) the way in which shopping trips are organized.

In the concluding chapter, the main research findings are summarized, and their most important implications – both for consumers and (different types of) retailers – are reflected on. Moreover, we also discuss the limitations of our analyses, and suggest potential directions for further research in the area of hard-discounters and multiple-store shopping.

Chapter 2 Close Encounter with the Hard-Discounter: A Multiple-Store Shopping Perspective on the Impact of Local Hard-Discounter Entry

2.1 Introduction

Over the past decade, one of the most striking developments in grocery retailing is the rise of the so-called hard-discounter format (HD hereafter). Several factors have allowed these no-frills price fighters to secure a considerable market share in many Western countries. First, the number of HD outlets has expanded rapidly over the years: exemplar chains Aldi and Lidl currently operate more than 18,000 outlets worldwide, while an additional 6,000 are projected to be opened by 2014 (Planet Retail 2010). Second, consumers have become increasingly receptive to the format, leading to its acceptance in low- and high-income segments alike (Steenkamp and Kumar 2009). Originally seen as a European phenomenon, HDs are now quickly making their way to US markets (Cleeren et al. 2010). While their share is still modest compared to mainstream US retailers, their growth figures are astounding (e.g. 21% in 2008 and 13.7% in 2009 for Aldi). As such, "… [this] new class of European Discounters have US retailers squarely in their sights" (Steenkamp and Kumar, 2009, p. 2), forcing traditional retailers to "pick up the gauntlet" (Planet Retail, 2010).

Yet, despite these pressing messages, there is a dearth of academic research on the HD format (see Cleeren et al. 2010 for an exception). Insights into how traditional chains are affected by HD entry, what drives these effects, and how they should be responded to, are yet to be developed. Available studies do investigate the impact of "large-discounter" entry (in particular: Wal-Mart), revealing that when a large-discounter enters a local market, traditional incumbents are severely hurt and incur sales losses of about 17% on average (Ailawadi et al. 2010, Gielens et al. 2008, Singh et al. 2006, Zhu, Singh and Dukes 2011). These losses primarily stem from defection of incumbents' best customers, and are most pronounced for incumbents close to the newly opened Wal-Mart store, either geographically or in terms of assortment composition (Ailawadi et al. 2010, Gielens et al. 2008, Singh et al. 2006). In response to such large-discounter entry, traditional supermarkets are advised to reduce assortment overlap, or to establish more competitive (Hi-Lo) prices (Ailawadi et al. 2010, Gielens et al. 2008).

Large-discounters strongly differ from hard-discounters, however. By capitalizing on their purchasing power and scale economies (Singh et al. 2006), large-discounters can keep prices low while simultaneously offering an extensive choice of (well-known) products. In contrast, savings at HDs come at the cost of lean, private-label dominated assortments (Steenkamp and Kumar 2009) that enable extremely efficient operations and even lower prices. This vastly different business model is likely to trigger different shopper responses, and call for different incumbent reactions. While large-discounters, with their broad and deep assortments, pose a full-fledged alternative to traditional supermarkets, the limited-range HDs are less likely to fully replace these supermarkets as the format-of-choice. Rather, consumers may choose to simultaneously "trade down" in some categories and "trade up" in others by visiting both formats in tandem (Costa et al. 2006). This makes hard-discounters complements to traditional supermarkets – rather than strict substitutes.

Such complementarity may entail a dual effect on (traditional) incumbents' clientele. On the one hand, it may increase the appeal of "multiple-store shopping" (MSS hereafter), and induce incumbents' loyal customers (single-store shoppers) to shift part of their purchases to the HD entrant. While these customers would not be entirely lost, their spending would be substantially reduced. On the other hand, customers who already visited the focal incumbent alongside another traditional chain, may now trade one of these chains for the new (more complementary) HD store. This, then, gives rise to two possible scenarios. If the focal incumbent is replaced, the customer and his spending are entirely lost. If, however, the focal incumbent remains in the store set alongside the HD, the customer and part of his spending is retained. Depending on which scenario prevails, the incumbent's losses after HD entry may thus be entirely different. Hence, more insights are needed into (i) how consumers' (multiple-store) shopping behavior changes when a HD enters the local market, (ii) what drives these behavior shifts and (iii) how this shapes proper response strategies for incumbent chains.

To provide these insights, we build on earlier work on multiple-store shopping (Popkowski Leszczyc, Sinha and Sahgal 2004, Gijsbrechts et al. 2008), and develop a conceptual framework in which consumers' patronage and spending allocation decisions depend not only on local outlet characteristics, but also on interactions between them. This enables a richer view on the competition between traditional and HD grocery chains: instead of regarding them as strict substitutes, we allow for complementary effects that may lead to their joint patronage. We then empirically test this framework using a unique data set of actual shopping behavior before and after a HD enters a local market.

The text is organized as follows. We first discuss the relevant literature and develop our conceptual framework. Next, we present the model, and describe the data and setting. We then report the estimation results and discuss their implications. The final section summarizes the main conclusions, and provides limitations and recommendations for further research.

2.2 Theoretical Background

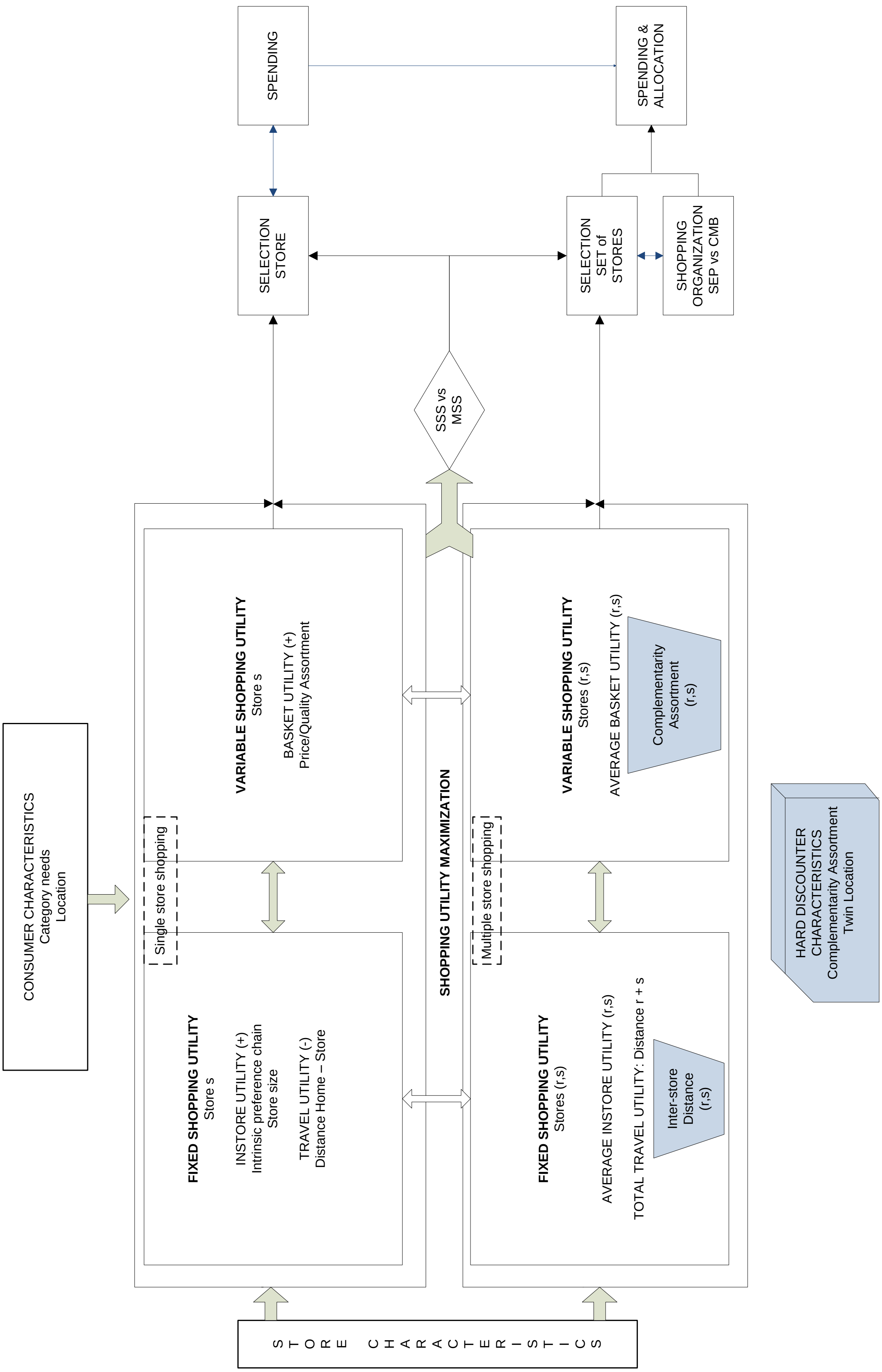
Related literature

Our work builds upon two streams of literature. The first stream bears on the advent of discounters in grocery retailing. Within this area, most scholars study how entry of a large-discounter such as Wal-Mart affects the performance of traditional supermarket chains, and generally find considerable post-entry sales drops (of up to 27%; Ailawadi et al. 2010, Singh et al. 2006). These losses are accounted for by a small fraction of customers (10% of the households accounting for 64 % of the observed losses) – implying that incumbents lose some of their best customers (Singh et al. 2006, p 459). Incumbents that exhibit large assortment overlap with the large-discounter entrant (i.e. offer the same product categories) and/or are located close to the large-discounter, suffer most (Ailawadi et al. 2010, Gielens et al. 2008). The second literature stream is that on grocery shopping behavior, with particular emphasis on multiple-store shopping, i.e. the systematic joint patronage of two or more stores to take advantage of the complementarities between them (Dellaert et al. 1998, Krider and Weinberg 2000, Gijsbrechts et al. 2008). While such behavior is less relevant for large-discounter entry, it may play an important role in assessing HD entry effects. Building on these two streams of literature, we present our conceptual framework below.

Conceptual framework

Grocery shopping patterns in the presence of multiple stores. Bringing together insights from earlier work by Bell, Ho and Tang (1998), Rhee and Bell (2002) and Gijsbrechts et al. (2008), Figure 2.1 offers a stylized representation of what drives consumers' grocery shopping patterns. The top part reflects the traditional view, in which consumers select the single store that maximizes their overall (fixed plus variable) shopping utility (Bell et al. 1998). Specifically, they choose the store with the lowest travel cost, unless the intrinsic appeal (in-store utility, stemming, e.g., from high service or enjoyable shopping ambience) or variable benefits and costs (basket utility, determined by the quality and price of the assortment) of a more remote store more than compensate for the larger distance (Berman and Evans 2010; Briesch, Chintagunta and Fox 2009; Ghosh and McLafferty 1984; Tang, Bell and Ho 2001).

FIGURE 2.1
Conceptual Framework



The bottom part of the figure adds a second possible decision path: that of multiple-store shopping. The underlying premise is that store choice decisions are not incidental and made on a visit-by-visit basis but, rather, are part of a more stable shopping pattern that maximizes consumer utility over a longer period (Gijsbrechts et al. 2008, Krider and Weinberg 2000). While single-store shopping can still be selected as the optimal pattern-of-choice, consumers can also decide to visit more than one store. This allows consumers to take advantage of store complementarities (i.e. different stores offering superior variable shopping utility in different categories; Gijsbrechts et al. 2008). By spreading their purchases across different stores, consumers can increase their overall basket utility – which may justify having to compromise on shopping convenience (e.g. because of larger travel costs). While multiple stores can be visited on separate occasions, consumers may also choose to visit them together on the same shopping trip. “Separate-trip” patterns generally require less time per shopping trip, and allow for a frequent replenishment of inventories (e.g. for perishable products) (Gijsbrechts et al. 2008; Krider and Weinberg 2000). In contrast, “combined-trip” patterns primarily help to reduce consumers’ travel costs (especially when the stores are located closely together; Dellaert et al. 1998), and allow consumers to exploit inter-store complementarities to the fullest (as they can buy every category in the store with the most attractive offer) (Dellaert et al. 1998; Gijsbrechts et al. 2008).

Taken together, Figure 2.1 shows two ways in which stores can become part of a consumer’s shopping pattern: either as the “single-best” option in which all of the grocery budget is spent, or as part of an appealing “store set” – that is either visited on separate or combined trips. When one store provides an overall advantage over all other stores, the store is more likely to become the single store-of-choice. When stores can only provide a partial variable utility advantage, for a subset of categories, they are more likely to be selected as part of a set of stores, especially when complementarity with other stores is high and extra travel costs low. These insights are particularly important to gauge the effects of HD entry.

Impact of hard-discounter entry. As indicated above, HDs constitute a new format, entirely different from the traditional retail business model, but also from large-discounters such as Wal-Mart. HD stores are small outlets (approximately 600 m2 in floor space), often located right next to (in "twin-location" with) traditional supermarket outlets (Foodmagazine 2009). They are characterized by lean assortments (holding about 1,000 to 1,500 SKUs, compared to 100,000 at Wal-Mart), and especially for fresh product categories such as meat and vegetables, the number of available product types is generally limited at best. In addition, a major share of these assortments is taken up by private labels (over 90% at Aldi, compared to only 38% at Wal-Mart) (Steenkamp and Kumar 2009). Together with a functional, no-frills store design and limited service, this allows HDs to keep costs down and charge even lower prices than large-discounters (up to 20% below Wal-Mart's, Wall Street Journal 2009).

With their lean and private label-dominated assortments, HDs do not provide a full-fledged substitute for traditional supermarkets, and are not likely to fully replace these supermarkets as the consumer's single store-of-choice. At the same time, however, the HD entrant is likely to be selected as part of a MSS pattern – as indicated by the shaded boxes in Figure 2.1. For one, the nature of the HD format makes MSS more rewarding in terms of basket utility. Given the limited number of SKUs per category and the absence of leading national brands, HDs cannot beat traditional supermarkets in categories where choice variety and brand equity play an important role (Briesch et al. 2009). Yet, they do have a competitive advantage in a subset of categories where price sensitivity is high: their strong price focus and back-to-basics assortment providing consumers with an easy, best price choice in those categories. Hence, HDs provide a highly complementary store offer. By purchasing at a HD as well as a traditional supermarket, consumers can combine large cost savings in price-sensitive categories with high-quality purchases in others ("trading up and down"), thereby enhancing their overall basket utility (Costa et al. 2006, Gijsbrechts et al. 2008). In addition, to the extent that HDs are located nearby traditional outlets, they make MSS – and especially combined-trip shopping – less costly in terms of extra travel time. This leads to interesting premises on the nature of incumbent losses from HD entry, and their underlying drivers.

First, as discussed above, HD entry is unlikely to stimulate primary store switching. Instead, consumers are more likely to visit the HD as part of a MSS pattern. As a result, a traditional chain is primarily at risk to lose its secondary customers to the HD entrant, that is: those consumers who already visited another supermarket alongside the chain, may now replace the latter with the new HD. In contrast (and unlike what was the case for large-discounter entry), the traditional chain is much less prone to entirely lose its best customers (i.e. those who bought their entire baskets at the chain before HD entry). Typically, these consumers will at most start visiting the HD alongside – rather than instead of – the traditional chain.

Second, while multiple-store shoppers who do replace the traditional chain with the HD are entirely lost as customers, they represent a smaller (relative) loss in spending (since only part of their basket was spent at the incumbent in the first place). In contrast, prior single-store shoppers who shift to MSS (with the new HD) are not entirely lost as customers, but can still substantially reduce their spending at the traditional chain.[1] Since recent sources indicate that a majority (>60%) of shoppers systematically engages in MSS nowadays (Gijsbrechts et al. 2008, IGD 2011), the first scenario seems the most likely one – indicating that traditional chains' (relative) spending losses from HD entry are likely to be smaller than their (relative) losses in customer count.

[1] Note that for MSS shoppers who stay with the incumbent, but now patronize it alongside the HD (instead of another traditional chain), we do not expect important spending shifts – as these households continue to spread their purchases across chains.

Third, consumers' sensitivity to price versus assortment is highly category-specific (Erdem, Swait and Louvière 2002; Inman, Shankar and Ferraro 2004) and, as indicated in a recent Nielsen study, many consumers want the "cheapest of the cheap" in some categories, while looking for "a wide selection of high quality brands" in others (Nielsen 2008, p. 3). Whereas the low-priced HD can perfectly meet consumers' demands for price-sensitive categories, its ability to fulfill assortment-related needs (quality, variety of choice) remains limited. Traditional chains, for which appealing assortments play a more central role in their selling proposition, seem better apt to satisfy these needs – and thus "complement" the HD's price focus. Therefore, the more a traditional chain prioritizes on its assortment, the more it complements HDs – and the more likely it becomes that, after HD entry, the chain will still be visited alongside the new HD. As such, the extent to which traditional chains lose customers to HDs, may be inversely related to their complementarity with this format.

Finally, the likelihood that consumers keep visiting a traditional chain after HD entry, may also depend on that chain's location vis-à-vis the new HD. Specifically, when a HD locates in the near vicinity of a traditional chain, the resulting "twin-location" strongly facilitates "one-stop shopping" – allowing consumers to spread their purchases across the two stores in an extremely convenient fashion. Hence, customers of traditional chains in immediate proximity of a HD are less likely to entirely defect, and more likely to visit both stores (on combined trips) instead (Brooks, Kaufmann and Lichtenstein 2004; Dellaert et al. 1998). This "ideal neighbor advantage" (De Volkskrant 1995; Foodmagazine 2009), however, does not apply to traditional chains located further away from the HD entrant. As such – in contrast to what was found for large-discounter entry – losses to HDs are not necessarily the most severe for incumbents in close proximity.

In sum, rather than completely lose their best customers (that is, customers who visited the chain in isolation) to HDs, traditional chains may primarily see "secondary" customers switch away. However, since these (multiple-store) shoppers were not loyal to the chain in the first place, the (relative) loss in spending to HDs is likely to be less severe than the (relative) loss of patronage. Moreover, we expect the number of customers actually lost upon HD entry, to remain fairly limited when the chain is strongly complementary and/or conveniently located vis-à-vis the new HD. In the next section, we present a methodology that allows for an empirical assessment of these expectations.

2.3 Methodology

We first present a base model in which households' shopping behavior, possibly involving multiple stores, is specified as a function of local store availability and characteristics. Next, we indicate how local HD entry is incorporated in the specification.

Base model

In line with the expected entry effects of HDs, we focus on households' monthly shopping pattern decisions, instead of individual trips. This allows us to uncover changes in systematic shopping behavior across multiple stores, rather than promotion-induced "cherry-picking" (Fox and Hoch 2005). Based on our conceptual framework (Figure 2.1), we assume that households face four interrelated choices: single- versus multiple-store shopping pattern, separate- versus combined-shopping organization (given MSS), store (set) choice, and spending-allocation across stores (given MSS). We model these choices in a nested fashion.[2]

Single- versus multiple-store shopping. Households can either choose to shop at a single store or buy their groceries at multiple stores. This choice can be expressed by a binary-logit model (layer A in Table 2.1), in which the utility of shopping at multiple stores is a function of the

[2] Note that even though we use a nested structure, this does not imply that consumers make the four choices strictly sequentially. Instead, we allow the decisions to be interrelated through the model's inclusive values.

TABLE 2.1
Model Specification

Layer A: Shopping pattern decision (MSS versus SSS)		
Model equation	**Utility specification**	**Specification of inclusive values**
$P_t^h(MSS) = \dfrac{e^{W_t^h(MSS)}}{e^{W_t^h(SSS)} + e^{W_t^h(MSS)}}$	$W_t^h(MSS) = \lambda_0 + \lambda_1 * Month_t + \zeta * IV_t^h(MSS)$ $W_t^h(SSS) = \zeta * IV_t^h(SSS)$	$IV_t^h(MSS) = \ln(e^{V_t^h(SEP)/\zeta} + e^{V_t^h(CMB)/\zeta})$; $IV_t^h(SSS) = \ln(\sum_{k=1}^{K_t^h} e^{U_t^h(k)/\zeta})$

Layer B: Trip organization decision (CMB versus SEP)		
Model equation	**Utility specification**	**Specification of inclusive values**
$P_t^h(CMB \mid MSS) = \dfrac{e^{V_t^h(CMB)/\zeta}}{e^{V_t^h(SEP)/\zeta} + e^{V_t^h(CMB)/\zeta}}$	$V_t^h(CMB) = \gamma_0 + \gamma_1 * Month_t + \xi * IV_t^h(CMB)$ $V_t^h(SEP) = \xi * IV_t^h(SEP)$	$IV_t^h(CMB) = \ln(\sum_{k=1}^{K_t^h-1} \sum_{l=k+1}^{K_t^h} e^{U_t^h(k,l \mid CMB)/\xi})$; $IV_t^h(SEP) = \ln(\sum_{k=1}^{K_t^h-1} \sum_{l=k+1}^{K_t^h} e^{U_t^h(k,l \mid SEP)/\xi})$

Layer C: Chain (set) choice decision		
Model equation	**Utility specification**	**Utility components (in-store+basket+travel)**[a]
$P_t^h(r \mid SSS) = \dfrac{e^{U_t^h(r)/\zeta}}{\sum_{k=1}^{K_t^h} e^{U_t^h(k)/\zeta}}$	$U_t^h(r) = instU^h(r) + bsktU_t^h(r) + trvlU^h(r)$	$instU^h(r) = \beta_{1,r} + \beta_2 * Size^h(r)$ $bsktU_t^h(r) = \beta_3 * ListAttr_t^h(r)$ $trvlU^h(r) = \beta_4 * \ln\left[Dist^h(r) + 1\right]$
$P_t^h(r,s \mid CMB) = \dfrac{e^{U_t^h(r,s \mid CMB)/\xi}}{\sum_{k=1}^{K_t^h-1} \sum_{l=k+1}^{K_t^h} e^{U_t^h(k,l \mid CMB)/\xi}}$	$U_t^h(r,s \mid CMB) = instU^h(r,s \mid CMB)$ $+ bsktU_t^h(r,s \mid CMB) + trvlU^h(r,s \mid CMB)$	$instU^h(r,s \mid CMB) = [instU^h(r) + instU^h(s)]/2$ $bsktU_t^h(r,s \mid CMB) = (1 + Comp_t^h(r,s))^{\psi} * [bsktU_t^h(r) + bsktU_t^h(s)]/2$ $trvlU^h(r,s \mid CMB) = \beta_4 * \ln\left[Dist^h(r,s \mid CMB) + 1\right]$
$P_t^h(r,s \mid SEP) = \dfrac{e^{U_t^h(r,s \mid SEP)/\xi}}{\sum_{k=1}^{K_t^h-1} \sum_{l=k+1}^{K_t^h} e^{U_t^h(k,l \mid SEP)/\xi}}$	$U_t^h(r,s \mid SEP) = instU^h(r,s \mid SEP)$ $+ bsktU_t^h(r,s \mid SEP) + trvlU^h(r,s \mid SEP)$	$instU^h(r,s \mid SEP) = [instU^h(r) + instU^h(s)]/2$ $bsktU_t^h(r,s \mid SEP) = (1 + Comp_t^h(r,s))^{\theta} * [bsktU_t^h(r) + bsktU_t^h(s)]/2$ $trvlU^h(r,s \mid SEP) = \beta_4 * \ln\left[Dist^h(r,s \mid SEP) + 1\right]$

Layer D: Spending allocation decision
Model equation
$\ln(\dfrac{m_t^h(r \mid (r,s), CMB)}{1 - m_t^h(r \mid (r,s), CMB)}) = \phi_1 * (instU^h(r) - instU^h(s)) + \phi_2 * (bskU_t^h(r) - bskU_t^h(s)) * (1 + COMP_t^h(r,s))^{\phi_3} + \vartheta_t^h(r \mid (r,s), CMB)$
$\ln(\dfrac{m_t^h(r \mid (r,s), SEP)}{1 - m_t^h(r \mid (r,s), SEP)}) = \varphi_1 * (instU^h(r) - instU^h(s)) + \varphi_2 * (bskU_t^h(r) - bskU_t^h(s)) * (1 + COMP_t^h(r,s))^{\varphi_3} + \vartheta_t^h(r \mid (r,s), SEP)$

[a] See Table 2.3 for details on the variable operationalizations.

overall attractiveness (captured by the inclusive values $IV_t^h(MSS)$ and $IV_t^h(SSS)$) of multiple- and single-store shopping (the "vertical" comparison in Figure 2.1). We control for evolutions in MSS independent of local market characteristics through the trend ($Month_t$).

Separate versus combined trips. Households that patronize multiple stores must decide how to organize their trips to these stores (see the right side of Figure 2.1 and layer B in Table 2.1). They can engage in separate-trips (i.e. visit the stores on separate shopping occasions) or combined-trips (i.e. make multi-stop trips including more than one store). Again, we use a binary-logit model to capture the choice between these two options, including as explanatory variables the inclusive values of combined and separate trips ($IV_t^h(CMB)$; $IV_t^h(SEP)$), as well as a trend variable controlling for exogenous evolutions in trip organization.

Store (set) choice. Another shopping decision faced by households is which store – or set of stores – to select. This decision is captured by a multinomial logit model (layer C in Table 2.1). Each (individual) store's utility comprises three components (see upper part of Figure 2.1): (i) in-store utility ($instU^h(r)$): benefits obtained from the physical environment or service in the store outlets (Berman and Evans 2010), (ii) travel (dis)utility ($trvlU^h(r)$): costs of covering the distance to the store (Fox, Montgomery and Lodish 2004), and (iii) basket utility ($bsktU_t^h(r)$): benefits and costs of purchasing one's basket (shopping list) of groceries at the store (Bell et al. 1998). For the drivers of these utility components: see Table 2.1 and the operationalization section below.

In line with our conceptual framework, households do not only extract utility from individual stores, but also from sets of stores. Consistent with Gijsbrechts et al. (2008), we restrict the maximum number of stores within a set to two. This greatly enhances tractability, while still allowing us to cover 90% of the sampled households' grocery spending. Like for individual store options, the utility of a store set is composed of: the in-store ($instU^h(r,s)$), travel ($trvlU^{h}(r,s)$), and basket utilities ($bsktU_{t}^{h}(r,s)$) of the store set (*r*,*s*). Travel utility associated with a set of stores is again a function of distance, be it that this variable now reflects the travel distance to be covered when visiting the set of stores – either on separate or combined trips (see Table 2.1). The latter option can help keep travelling costs minimal, especially when the distance between stores is small. In-store utility from a set of stores is given by the mean of the stores' individual in-store utilities (see Table 2.1). In line with prior multiple-store shopping literature (Krider and Weinberg 2000), we thereby assume there are no synergies between stores' in-store benefits. While a similar specification could be used for a store set's basket utility, this would ignore category-based complementarities between the stores ($Comp_{t}^{h}(r,s)$). As indicated above: by buying each category in the most appealing store for that category, households can increase their total basket utility. Hence, we augment a store set's basket utility with a "correction" for the degree to which the stores in the set complement each other (see Table 2.1). As the degree to which consumers can capitalize on these complementarities (i.e. allocate each category purchase to the store with the most attractive offer) may depend on the shopping organization, we allow the parameters θ and ψ to differ between separate- and combined-trip patterns. The complementarity construct is a key component of our model. We will discuss this construct in detail in the next section.

Spending allocation across stores in the set. Households that opt to visit a set of stores, must decide how to allocate their purchases across these stores. As indicated in Table 2.1 (layer D), we model this decision using a logistic specification. In this model, the household's spending share at store *r*, given that this store is patronized along with store *s*, depends on the difference in in-store utility and basket utility (corrected for complementarity) between the stores (Gijsbrechts et al. 2008, Inman et al. 2004, Zhang, Gangwar and Seetharaman 2010). Like for store set choice, we allow the parameters of this spending equation to differ for separate- and combined-trip organizations. Similar to Zhang and Krishnamurthi (2004) and

Zhang and Wedel (2009), we assume that the error term of the spending model has a logistic distribution and allow it to be correlated with the store set choice errors (see Appendix 1).

Incorporating Hard-Discounter Entry

Local entry of a HD outlet will affect the specification in several ways. First, the new HD outlet may either belong to a chain that was previously unavailable to the household, or to a chain that the household already had access to – but that is now expanding its local presence. In the former scenario, new options will be added to the household's consideration set at model layer C. The HD then comes in as an extra individual store alternative. It also forms a store set with each incumbent chain – to which part of the household's purchases can then be allocated (layer D). In the latter case, no additional shopping options become available. Instead, the new outlet (or store sets involving this outlet) may replace existing options in the household’s consideration set, for example when the new HD outlet is more conveniently located vis-à-vis the household (or other stores) than the chain’s current outlets.

Second, HD entry may have a differential effect on the choice probability of incumbent stores, as their probability of being chosen as part of a store set also depends on the complementarity and distance to the new HD (cf. Figure 2.1). Finally, all of the above changes affect model layers B (separate- versus combined-trip organization) and A (single- versus multiple-store pattern) through the inclusive values. We note again that, because the HD has high complementarity with traditional supermarkets, we expect store sets involving a HD and a traditional store to have high appeal, and – possibly – to increase MSS.

Estimation

We estimate the model parameters using simulated maximum likelihood. Unobserved household heterogeneity is incorporated by a latent class approach in which all parameters (except the trend parameters at model layers A and B, and the error correlation parameter at layer D) may vary across segments. As stated by Andrews, Ainslie and Currim (2002) and

Zhang and Wedel (2009), this finite mixture specification is empirically equivalent to the use of continuous mixing distributions. Details on the likelihood are given in Appendix 1.

2.4 Data and Operationalizations

Setting and Sample

To assess the impact of local HD entry, we use data on outlet openings of two HD chains in the Netherlands, between May 2002 and August 2006. We obtain these data from Reed Business, which – every 3 to 4 months – tracks all outlets of the main Dutch grocery retailers, along with their size and location. Taken together, our data cover 54 Aldi and 140 Lidl entries. Similar to Hwang, Bronnenberg and Thomadsen (2010), we define the local markets in which these HDs operate as circular areas around the HDs, with a 5 km radius. Openings and closures of non-HD outlets are also obtained from the Reed Business data.

To track shopping behavior before and after local HD entry, we use scanner purchase records from GfK's national household panel. From these data, we obtain households' shopping patterns, category needs and geographical location. To reduce model complexity, we only use purchases made in the top 9 grocery chains in the Netherlands, covering 78% of sales. Besides Aldi and Lidl, these include seven traditional players. Table 2.2 shows that while these traditional chains are not uniform in positioning (some being more upscale, e.g. Albert Heijn, others being more price-oriented, e.g. Jumbo), their wider assortments and higher prices make them very distinct from HDs. Our sample consists of households who (i) live in one of the 194 local markets, (ii) participated in the panel for the entire period 2002-2006 and (iii) purchase over 80% of their groceries in the chains under study. This leaves us with 703 households: split up into a calibration and holdout sample of 600 and 103 households, respectively. For each household, we observe 56 months of purchases, leaving us with a total of 39,368 observations – of which 17,535 (21,833) occur before (after) HD entry.

TABLE 2.2
Chain Descriptives

Grocery chain	% of sales	Average outlet size (m^2)	Category price (standardized)	Category size (standardized)	Category %PL (standardized)
Traditional chains					
Albert Heijn	20.2%	1,200	1.017	1.465	1.100
C1000	15.5%	876	.362	.902	-.512
Dirk	6.5%	1,074	.085	-.104	-1.149
Edah	4.7%	994	.166	-.121	.720
Jumbo	3.8%	1,104	.136	.154	-.238
Plus	3.9%	845	.347	-.101	-.025
Super de Boer	7.4%	930	.582	.580	.104
Hard-discounters					
Aldi	11.0%	430	-1.157	-1.373	-
Lidl	4.6%	627	-1.090	-1.403	-

Operationalizations

Consideration set. Following Fox et al. (2004), we delineate households' consideration sets based on distance. Consistent with our definition of outlets' trading areas, a household *h*'s consideration set in month *t* includes only stores within a 5 km radius from its residence (forming the set K_t^h). Moreover, when multiple outlets of the same chain are available within this 5 km radius, we assume that consumers consider those outlets that minimize travelling distance for any shopping pattern involving the chain. For single-store shopping patterns, and MSS patterns involving separate trips, this is the outlet closest to the customer's home. For MSS-combined trip patterns, outlets that minimize the chained-trip distance are considered.

Dependent variables. Within any month, similar to Gijsbrechts et al. (2008), we classify a household's shopping pattern as single-store if more than 80% of its total grocery spending occurred in a single chain, and as multiple-store otherwise. We further classify a multiple-store pattern as combined-trip if more than half of the spending occurred on chained trips, and as separate-trip otherwise.[3] To identify a household's store (set) of choice, we determine the chain (set) where the largest share of monthly grocery spending occurred. The dependent variable of the spending share model – explaining the allocation of grocery purchases over a selected set of stores r and s in month t – is measured as the amount spent in that month in the first store (r), divided by the amount spent at both stores.

Explanatory variables. In line with our conceptual framework, we include in-store utility, travel (dis)utility, basket utility and complementarity as explanatory variables in the choice model. Given our objective to (i) explain consumers' choice of shopping patterns, as well as (ii) shifts in these patterns following HD entry, we do not include previous choice as an explanatory variable (see Bell and Lattin 1998 and Fox et al. 2004 for a similar approach). As indicated by Bell and Lattin (1998, p. 79), such a last choice variable would already reflect most of the effects of in-store, travel and basket utility, and would not permit us to separate them out. Our model, in contrast, enables us to uncover how the chains' relative location and complementarity explain consumers' shopping behavior, before and after HD entry. We will revisit the effect of "last choice" in the robustness checks.

In-store and travel utility. We capture in-store utility through segment-specific intercepts for each store chain. These intercepts reflect the intrinsic preference for the chain "based on factors related to general positioning (service level, friendliness), operational policies, and overall excellence in execution" (Fox et al. 2004, p. S36). In addition, to accommodate differences in outlet size within each chain, we include outlet selling surface, measured in 1000 m^2. Travel distances are operationalized by using the Euclidean distances between household and outlet zip-codes, as further indicated in Table 2.3. Similar to Briesch et al. (2009), we log-transform these distances to accommodate decreasing marginal effects.

[3] We define "chained trips" as shopping occasions on which more than one chain was visited at the same part of the day (i.e. morning, afternoon, or evening), the most detailed time frame in the GfK data.

TABLE 2.3
Variable Operationalizations

Notation	Variable name	Operationalization
In-store utility		
$Size^h(r)$	*Selling surface*	Floor size of store *r* (considered by household *h*) in $1000m^2$
Basket utility		
$ListAttr_t^h(r)$	*Shopping list attraction*	Composite variable, reflects attractiveness of purchasing all groceries on monthly shopping list in store *r*. Computed as: $\sum_{c=1}^{C} w^h(c) * Attr_t(c,r)$
$w^h(c)$	*Category weight*	Category *c*'s value share in household *h*'s grocery spending across observation period
$Attr_t(c,r)$	*Category attraction*	Attractiveness of purchasing category *c* in store *r*. Computed as: $\delta_{A,c} * Assort_t(c,r) + \delta_{P,c} * Price_t(c,r) + \delta_{PL,c} * PLshare_t(c,r)$
$Assort_t(c,r)$	*Category assortment size*	Number of unique SKUs sold (as observed in panel data) in category *c* by store *r* in month *t* (standardized across both chains and months)
$Price_t(c,r)$	*Category price level*	Average price per volume unit, across all SKUs[a] sold (as observed in panel data) in category *c* by store *r* in month *t* (standardized across both chains and months)
$PLshare_t(c,r)$	*Category private label share*	Share of private label SKUs (as observed in panel data) in category *c* and store *r* in month *t* (standardized across both chains and months)
$Comp_t^h(r,s)$	*Inter-store complementarity*	"Degree" of complementarity between stores *r* and *s*. Computed as: $\dfrac{\sum_{c=1}^{C} w^h(c) * \lvert Attr_t(c,r) - Attr_t(c,s)\rvert - \left\lvert \sum_{c=1}^{C} w^h(c) * (Attr_t(c,r) - Attr_t(c,s))\right\rvert}{\max(k,l) \sum_{c=1}^{C} w^h(c) * \lvert Attr_t(c,k) - Attr_t(c,l)\rvert}$
Travel utility		
$\Delta(x,y)$	*Geographical distance*	Euclidean distance between geographical locations *x* and *y*, measured in 10km
$Dist^h(r)$	*Single-store pattern travel distance*	$2 * \Delta(h,r)$ (i.e. distance from household *h*'s home to store *r*; and back.)
$Dist^h(r,s \mid SEP)$	*Separate-trip pattern travel distance*	$[2 * \Delta(h,r) + 2 * \Delta(h,s)] * .75$ (i.e. distance from household *h*'s home to store *r* and back + distance from household *h*'s home to store *s* and back.) This distance is multiplied by .75: the middle between separate-trip shoppers engaging in twice as many trips, or in the same number of trips, as single-store shoppers.
$Dist^h(r,s \mid CMB)$	*Combined-trip pattern travel distance*	$\Delta(h,r) + \Delta(r,s) + \Delta(h,s)$ (i.e. distance from household *h*'s home to store *r* + distance from store *r* to store *s* + distance from store *s* back to household *h*'s home.)

[a] For each SKU, the price per volume unit is a weighted average of promotional and non-promotional prices, with the weights being the number of times these prices were observed.

Basket utility. The "shopping list attraction" that store *r* provides to household *h* in month *t*, is computed as a weighted average of the attractiveness of all product categories in the store:

$$ListAttr_t^h(r)$$
$$= \sum_{c=1}^{C} w^h(c) * Attr_t(c,r) = \sum_{c=1}^{C} w^h(c) * [\delta_{A,c} * Assort_t(c,r) + \delta_{P,c} * Price_t(c,r) + \delta_{PL,c} * PLshare_t(c,r)]$$

with weights $w^h(c)$ equal to the categories' shares in the household's grocery spending throughout the observation period (see also Fox et al. 2004). We use the GfK category classification, which covers a wide variety of products including food and non-food items, small- and big-ticket items, and categories with low and high levels of product differentiation (the full list of 52 categories can be found in Table A.2 in Appendix 2). All categories are sold in each of the nine chains under study – be it that assortment depth within each category may strongly differ. Following Briesch et al. (2009), the category attractions $Attr_t(c,r)$ are further specified as a function of assortment size $Assort_t(c,r)$ and price levels $Price_t(c,r)$ (see Table 2.3 for their operationalization). For the traditional supermarket chains, we include the assortment share taken up by the store brand $PLshare_t(c,r)$ as an additional explanatory variable (Dhar, Hoch and Kumar 2001).[4] The parameters, $\delta_{A,c}$, $\delta_{P,c}$ and $\delta_{PL,c}$ reflect category-specific assortment, price and store-brand sensitivities. Estimating these parameters simultaneously with the shopping pattern choice parameters would make the model exceedingly complex. Therefore, similar to Bell and Lattin (1998), we assess them through separate, category-level models, linking the portion of households' category outlay spent in a chain on the one hand, to that chain's category price, assortment, store-brand share (and two control variables) on the other (see Appendix 2 for details). In total, 52 such models were run (one for each category), with 5 parameters each. The number of observations for estimation (each observation representing a household's category outlay within a certain month) ranges from 1,823 (for diet products) to 38,301 (for vegetables).

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[4] This variable is not relevant for HD chains, whose assortment consists almost exclusively of private labels.

Store complementarity. As outlined above, a key driver of MSS (and of the impact of HD entry) is store complementarity: the fact that two stores may have strong appeal in different categories such that, taken together, they constitute an attractive combination. Our measure of store complementarity builds on constructs developed in previous literature on the variety and complementarity of products in an assortment (Rooderkerk, Van Heerde and Bijmolt 2011, Van Herpen and Pieters 2002). Rooderkerk et al. (2011), in their study of assortment context effects, quantify both (i) product dissimilarity (to what extent do product attributes differ from those of other items in the assortment), and (ii) product dominance (to what extent are products superior in their attributes to other available options). Similar dimensions are used by Van Herpen and Pieters (2002). While our setting is completely different (store chains with differences in category attractiveness, as opposed to products in an assortment with different attribute levels), the same notions apply, in that the degree of complementarity between two chains depends on (i) the magnitude of differences (dissimilarities) in category attractiveness (positive effect) and (ii) the extent to which one store is consistently superior to (dominates) the other (negative effect). With this in mind, we construct the following measure of complementarity between store *r* and *s*, for household *h* at time *t*:[5]

$$Comp_t^h(r,s) = \frac{\sum_{c=1}^{C} w^h(c) * \left| Attr_t\ (c,r) - Attr_t\ (c,s) \right| - \left| \sum_{c=1}^{C} w^h(c) * (Attr_t\ (c,r) - Attr_t\ (c,s)) \right|}{\max(k,l) \sum_{c=1}^{C} w^h(c) * \left| Attr_t\ (c,k) - Attr_t\ (c,l) \right|}$$

The first term in the numerator reflects the "dissimilarity" factor, and sums the stores'

[5] Van Herpen and Pieters (2002) propose an attribute-based measure that comprises two components: the dispersion of attribute levels over different products (i.e., how strongly do attributes differ across products), and the dissociation of attribute levels (to what extent do different combinations of attributes occur in different products). Note that the specifics of our complementarity construct are quite different from previous authors': Van Herpen and Pieters (2002) quantify the variety in a complete assortment, and Rooderkerk et al. (2011) compute the attribute-based similarity and dominance of a product compared to the total assortment. In contrast, the complementarity measure that we propose compares the assortment of two grocery chains, taking the price/quality position of different categories into account. Also, whereas Van Herpen and Pieters (2002) consider attributes with a discrete number of levels, our category attractions are continuous.

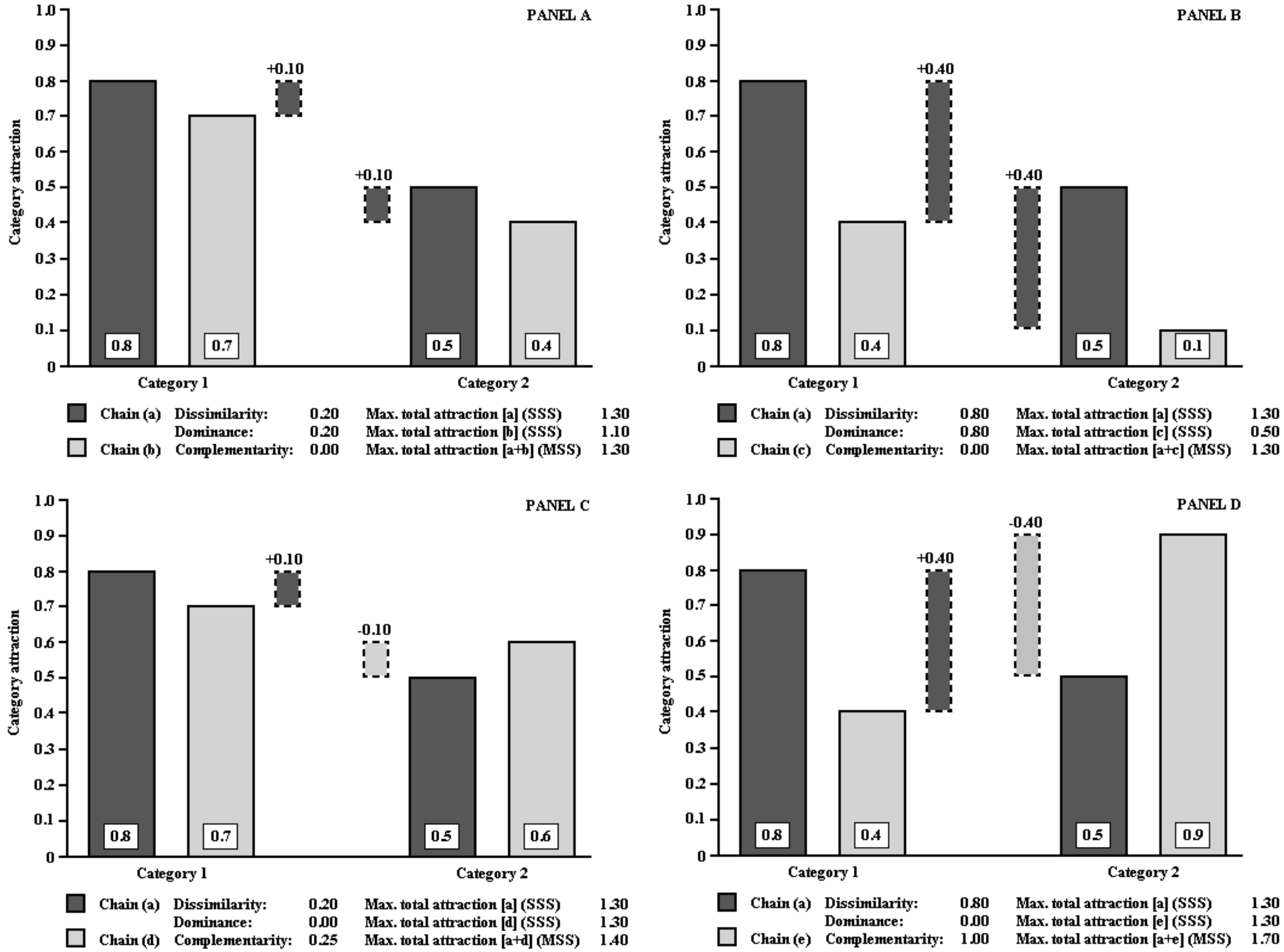
absolute differences in attractiveness across categories (weighed by their share in household grocery spending).[6] The less the stores resemble each other in terms of category appeal, the larger this sum becomes. The second term represents the "dominance" factor, which goes up when one store has the highest appeal for a larger number of categories. It is again a weighted sum of differences in category attractiveness. However, by summing up the actual differences (rather than their absolute values), positive (store *r* outperforming *s*) and negative differences (store *s* outperforming *r*) can cancel each other out. Hence, as households' preferences for both stores become more balanced across categories (i.e. both stores being the superior option for a different set of categories), the dominance term becomes smaller, and complementarity goes up. In contrast, if one store is preferred over (dominates) the other in all categories, the second term equals the first, and complementarity is zero. The denominator simply rescales the measure to the [0-1] range. Figure 2.2, panels A-D, graphically illustrate the meaning of our complementarity measure, for a stylized setting with two categories. Each panel represents a scenario in which a hypothetical store (a) and another store (b to e) differ in category attractiveness. The panels show how variations in dissimilarity and dominance lead to differences in complementarity. For each scenario, the figure also compares the maximum obtainable attraction across categories (assuming equal category weights) under single and multiple-store shopping patterns, and shows that MSS patterns can provide higher utility than single-store patterns as complementarity goes up.

Hard-discounter entries

Table 2.4, panel A reports, for each chain, the percentage of visits on single-store, separate-trip multiple-store, or combined-trip multiple-store shopping patterns. It shows that for each chain, more than 50% of visits occur within multiple-store patterns. These figures

[6] Unlike Rooderkerk et al. (2011), we use a city block distance metric; using absolute instead of squared differences. This appears more appropriate, given that we integrate evaluations of different product categories, which are "highly analyzable, and remain psychologically distant when in combination" (Nosofsky 1986).

FIGURE 2.2
Example of Complementarity[a] Measure: Dissimilarity, Dominance and Total Attraction



[a] The denominator of our complementarity measure (see page 32) is computed over all possible chain pairs in this example (i.e. chains (a) to (e)).

TABLE 2.4
Distribution of Shopping Patterns

PANEL A: DISTRIBUTION OF PATTERNS ACROSS CHAINS

Grocery chain	Single-store	Multiple-store		
		Separate-trip	Combined-trip	Total MSS
Traditional chains				
Albert Heijn	41.4%	46.5%	12.1%	58.6%
C1000	31.2%	53.2%	15.6%	68.8%
Dirk	25.5%	58.6%	15.9%	74.5%
Edah	16.5%	64.6%	18.9%	83.5%
Jumbo	19.8%	60.4%	19.8%	80.2%
Plus	42.9%	46.8%	10.3%	57.1%
Super de Boer	30.8%	56.9%	12.3%	69.2%
Hard-discounters				
Aldi	8.0%	66.9%	25.1%	92.0%
Lidl	3.7%	66.4%	29.9%	96.3%

PANEL B: DISTRIBUTION & TRANSITION[a] OF PATTERNS ACROSS TIME

		POST-ENTRY (600 HH)						
		Single-store		Separate-trip		Combined-trip		Total
PRE-ENTRY (600 HH[b])		(No HD)	(HD)	(No HD)	(HD)	(No HD)	(HD)	
Single-store	**(No HD)**	35.5%	0.2%	6.1%	3.8%	0.3%	0.9%	46.9%
	(HD)	0.0%	0.7%	0.0%	0.6%	0.0%	0.2%	1.5%
Separate-trip	**(No HD)**	4.8%	0.2%	13.5%	4.1%	0.7%	0.3%	23.6%
	(HD)	1.2%	0.3%	1.3%	14.2%	0.0%	1.7%	18.7%
Combined-trip	**(No HD)**	0.5%	0.0%	0.9%	0.2%	2.0%	0.6%	4.1%
	(HD)	0.0%	0.0%	0.3%	0.9%	0.0%	4.0%	5.3%
Total		42.0%	1.4%	22.1%	23.8%	3.0%	7.7%	

[a] The transitions depicted are between households' "dominant" shopping patterns (i.e. most commonly chosen) in the pre- and post HD-entry periods.
[b] While all 703 households in our sample reside less than 5 kilometers away from at least one hard-discounter outlet opening, not all households include these outlets in their consideration set (e.g. because they have another outlet of the same HD chain closer by than the entrant), explaining the lower number of households used for the pre- and post-entry comparisons.

are especially high for Aldi and Lidl (92.0% and 96.3%, compared to a 70.3% average across traditional supermarkets). It follows that the entry of these HDs is likely to enhance multiple-store shopping. Further support for this notion is lent by Table 2.4, panel B, which depicts the prevailing shopping patterns before and after HD entry – and how households transit between them. While the majority of households (70%) does not switch to a different type of shopping pattern after a HD opens up, the table shows that if households decide to visit a HD (in response to HD entry), they are most likely to do so by means of a multiple-store pattern. As a result, the table shows that the total number of multiple-store shopping households has increased after HD entry (from 51.7% to 56.7%).

The emerging picture thus is that HD entry indeed leads to more MSS. Yet, the question remains how it affects the patronage and spending at incumbent supermarkets and, especially, how this impact depends on the stores' location and complementarity vis-à-vis the HD. The model outcomes will shed light on these issues.

2.5 Results

Category attractions and complementarities

We first discuss the estimation results for the auxiliary category-attraction equations, used to compute store-specific shopping list attractions (see Table A.1 in Appendix 2). In line with expectations, the assortment coefficients are significantly positive for 37 (out of 52) categories, while significant and negative price effects are found in 41 categories. The PL-share coefficients are mostly negative (39 parameters negative significant), but this is only a partial effect: the (positive) impact of lower PL prices already being captured through the price coefficient. For 31 categories, households respond more strongly to assortment size, while price response dominates in the remaining 21 categories.[7] This supports the notion that consumers "trade up" for some products and "trade down" for others. The resulting pattern of category attractions (see Table A.2 in Appendix 2) confirms that HDs have a comparative advantage in a subset of price-sensitive categories, yet tend to be less attractive in categories

[7] Note that since these variables are standardized, their coefficients can be compared.

where product quality and/or choice variety play a more important role. Overall, the results have face validity, and constitute a sound input for our complementarity construct.

Table 2.5 displays the resulting degree of complementarity for each chain pair in our data set, averaged across households and time. First, it shows that for each traditional chain, complementarity is far stronger with the HDs than with other supermarkets. Second, complementarity between the two HDs is low, indicating that it is most prevalent across store formats. Third, among the traditional chains, a distinction emerges between high-end chains (such as Albert Heijn, see also Table 2.2), and those that are more price-oriented (like Jumbo). The latter chains exhibit lower complementarity with the HD stores, a result that makes intuitive sense and supports the validity of our measure.

TABLE 2.5
Complementarities by Chain Pair

	Traditional							**Hard-discount**	
	Albert Heijn	**C1000**	**Dirk**	**Edah**	**Jumbo**	**Plus**	**Super de Boer**	**Aldi**	**Lidl**
Albert Heijn	-								
C1000	.282	-							
Dirk	.170	.195	-						
Edah	.157	.197	.165	-					
Jumbo	.195	.241	.115	.169	-				
Plus	.124	.130	.184	.155	.109	-			
Super de Boer	.094	.155	.211	.210	.197	.130	-		
Aldi	.734	.755	.298	.297	.436	.345	.550	-	
Lidl	.697	.740	.350	.352	.492	.399	.616	.131	-

Shopping pattern choice and spending allocation

Based on the BIC criterion, the three-segment solution is retained (BIC=6748.9, compared to 6784.5 and 6806.6 for the two and four segment model, respectively). With a hit rate of 35.9% and an average hit probability of 56.1%, the model also exhibits high predictive validity in the holdout sample.

Table 2.6 reports the parameter estimates for the 3 segments (with sizes of 36.9%, 26.3% and 36.8%). Overall, the estimates provide support for the conceptual framework and are in line with previous store choice literature. At model layer C (store (set) choice), the chain intercepts that capture the chains' overall appeal (relative to market leader Albert Heijn), point to substantial differences in intrinsic store preferences across chains and consumer segments. At the same time, stores are more likely to be included in households' shopping patterns when they are larger in size, provide greater shopping list attraction, and are located closer to the household. These factors enhance selection of the store as a single shopping destination, but also as part of a MSS pattern – as illustrated in Table 2.7, panel A, which displays the % change in visit probability for two incumbents (high-end: Albert Heijn, price-oriented: Jumbo), triggered by a 10% increase in their list attraction (the elasticity expressions are derived in Appendix 3). For sets of stores (MSS patterns), the complementarity parameter is strongly significant and positive in 5 out of 6 cases, indicating that the more complementary two stores are, the more attractive it is to visit both of them.[8]

The positive and significant inclusive value parameters transfer such increases in store set utility to model layers B and A. The intercepts at these layers point to a strong tendency towards MSS (positive significant layer-A intercept λ_0 for segments 1 and 3, encompassing 73.7% of the shoppers) and towards visiting different chains on separate rather than combined trips (negative layer-B intercept γ_0 for all segments).

A closer look at the segment differences shows consumers in segment 1 to be more likely to engage in MSS than those in segment 2. Interestingly, they also have the most positive attitude towards Aldi and Lidl, and are most sensitive to store complementarities. In contrast, segment 2 primarily consists of single-store shoppers, with a strong preference for upscale stores, resistance to cover larger distances and low sensitivity to complementarities.

[8] In estimating the utility-maximizing shopping pattern model, we do not posit that consumers actually use all the detail included in the measures that enter this model. Still, the literature on cognitive psychology suggests that consumers, in their own way, may be able to form beliefs about the key constructs in our model, and use them to guide their shopping behavior along the proposed lines. Our finding that the estimated effects are significant and in line with expectations corroborates this.

TABLE 2.6
Parameter Estimates

	Parameter		**S1** (36.9%)	**S2** (26.3%)	**S3** (36.8%)
Layer A	Intercept	(λ_0)	***1.440***[a]	***-1.104***	***.263***
Choice for MSS			(91.776)	(-87.375)	(20.942)
(vs. SSS)	Monthly trend	(λ_1)	***.050***	***.050***	***.050***
			(12.811)	(12.811)	(12.811)
	Incl. value	(ζ)	***.163***	***.085***	***.185***
			(11.332)	(33.373)	(23.685)
Layer B	Intercept	(γ_0)	***-.208***	***-.215***	***-.315***
Choice for			(-12.162)	(-18.188)	(-24.551)
combined trips	Monthly trend	(γ_1)	***.014***	***.014***	***.014***
(vs. separate trips)			(10.463)	(10.463)	(10.463)
	Incl. value	(ξ)	***.104***	***.224***	***.174***
			(11.657)	(33.790)	(24.093)
Layer C	**In-store utility**				
Choice of	Albert Heijn (reference)				
chain / chain set	Aldi	($\beta_{1,1}$)	***.608***	***-.312***	***-.952***
			(11.617)	(-25.956)	(-23.291)
	C1000	($\beta_{1,2}$)	***.382***	***.346***	***-.729***
			(11.556)	(33.382)	(-23.635)
	Dirk	($\beta_{1,3}$)	***.717***	***-.293***	***.336***
			(11.623)	(-16.779)	(23.482)
	Edah	($\beta_{1,4}$)	***.320***	***.187***	***-.614***
			(11.548)	(24.871)	(-23.434)
	Jumbo	($\beta_{1,5}$)	***.471***	**-.041**	***-.241***
			(11.534)	(-1.996)	(-21.575)
	Lidl	($\beta_{1,6}$)	***.369***	***-.271***	***-1.287***
			(11.592)	(-23.197)	(-23.243)
	Plus	($\beta_{1,7}$)	***.162***	***-.127***	***.076***
			(11.142)	(-16.717)	(14.065)
	Super de Boer	($\beta_{1,8}$)	***.250***	***.228***	***-.408***
			(11.482)	(29.251)	(-24.016)
	Selling surface	(β_2)	***.028***	***.197***	***.031***
			(9.619)	(32.781)	(16.482)
	Basket utility				
	List attraction	(β_3)	***.202***	***1.043***	***1.278***
			(9.596)	(27.309)	(23.079)
	Travel utility				
	Travel distance	(β_4)	***-.925***	***-2.614***	***-1.551***
			(-11.666)	(-34.243)	(-24.151)
	Complementarity				
	Separate trips	(θ)	***1.036***	***.456***	***.706***
			(25.668)	(24.272)	(69.275)
	Combined trips	(ψ)	***1.099***	.113	***.693***
			(24.525)	(1.676)	(52.983)
Layer D	**Difference in in-store utility**				
Allocation of	Separate trips	(φ_1)	-.018	**.066**	***.162***
spending			(-1.232)	(2.471)	(17.418)
	Combined trips	(ϕ_1)	.057	.149	***.102***
			(1.112)	(1.347)	(3.805)
	Difference in basket utility				
	Separate trips	(φ_2)	.120	.251	.198
			(.492)	(.589)	(.671)
	Combined trips	(ϕ_2)	1.171	2.198	**1.677**
			(1.612)	(1.242)	(2.104)
	Complementarity				
	Separate trips	(φ_3)	-2.380	-1.284	-1.831
			(-.215)	(-.149)	(-.199)
	Combined trips	(ϕ_3)	-1.369	-.752	-1.062
			(-.507)	(-.231)	(-.343)
	Error correlation	(χ)	.003	.003	.003
			(.254)	(.254)	(.254)

[a] Estimates significant at the 5% and 1% level (two-sided) are portrayed in bold and italics, respectively. Values in brackets represent t-values for the coefficients.

TABLE 2.7
Impact of Changes in List Attraction, Complementarity and Inter-Store Distance[a]

Incumbent	*Albert Heijn*				*Jumbo*			
	Segm. 1	Segm. 2	Segm. 3	All	Segm. 1	Segm. 2	Segm. 3	All[b]
PANEL A: IMPACT OF A 10% INCREASE IN LIST ATTRACTION FOR THE INCUMBENT								
% change in probability to visit incumbent:								
in any MSS pattern	1.54%	3.04%	5.27%	3.30%	4.84%	9.80%	16.74%	10.53%
overall	2.53%	17.07%	11.87%	9.79%	4.85%	17.47%	18.81%	13.30%
PANEL B: IMPACT OF A 10% INCREASE IN COMPLEMENTARITY BETWEEN THE INCUMBENT AND LIDL								
% change in probability to visit incumbent:								
in MSS (separate or combined) pattern with Lidl	2.18%	1.42%	4.63%	2.88%	1.34%	0.93%	2.96%	1.83%
in any MSS pattern	.12%	.06%	.26%	.16%	.16%	.08%	.33%	.20%
overall	.08%	.04%	.16%	.10%	.12%	.06%	.26%	.16%
PANEL C: IMPACT OF DISTANCE REDUCTION BETWEEN INCUMBENT AND LIDL, FROM .5 KM TO TWIN-LOCATION (0 KM)								
% change in probability to visit incumbent:								
in combined pattern with Lidl	33.69%	46.91%	34.09%	37.31%	34.24%	45.23%	34.35%	37.17%
in any MSS pattern	2.28%	3.31%	2.37%	2.59%	4.86%	6.38%	4.88%	5.27%
overall	1.49%	2.09%	1.52%	1.66%	3.89%	5.10%	3.90%	4.21%

[a] Figures in the table refer to relative probability changes, i.e. % changes compared to the current level.
Calculations based on the elasticity expressions (see Appendix 3), for average levels of the variables in those expressions across the entire data set.
[b] Weighted average across the three segments, using segment sizes as weight.

While complementarity plays a key role in store selection of multiple-store shoppers and, through the inclusive values, can drive up MSS, its parameters in the spending share model are not significant. This needs to be interpreted against the fact that the (conditional) spending share model is parameterized only on chains that do co-occur in a MSS pattern, and for which complementarities are already high in the first place. It is also in line with the distribution of actual spending shares among stores in a MSS set, which has a strong mass point around .5, with a small deviation. Still, the spending model estimates reveal that, given store set selection, consumers spend relatively more at larger stores (positive significant parameter for selling surface in 3 out of 6 cases).

Implications for HD entry effects. The estimation results in Table 2.6 already shed light on the likely effects of HD entry. HDs provide greater complementarity-advantages than traditional stores (cf. Table 2.5), thereby increasing the probability that a store set including the HD will be chosen and – through the inclusive values – the tendency to visit multiple stores. Based on the positive complementarity-coefficient, incumbents that are more complementary to the HD are more likely to be selected in such a MSS pattern alongside the HD. This is further documented in Table 2.7, panel B, which shows the % change in visit probability for Albert Heijn and Jumbo that would result from a 10% increase in their current complementarity with Lidl. From this table, it becomes apparent that even if the incumbents' list attraction remains unchanged, the mere increase in complementarity enhances their combined shopping propensity with Lidl (on average: by 2.88% for Albert Heijn and 1.83% for Jumbo), and even slightly increases their patronage in any MSS pattern (+.16% for AH, +.20% for Jumbo) and overall (+.10% for AH, +.16% for Jumbo). Moreover, over and above this partial effect, complementarity will substantially enhance the impact of increases in incumbents' list attraction, on their probability of being selected alongside the HD (see Appendix 3) – as we will show in the implications section.

The negative coefficient of store distance already suggests that location close to a traditional supermarket – which is quite common for HD entrants – may facilitate combined-trip MSS, by allowing consumers to take advantage of store complementarities while keeping travel cost increases under control. Table 2.7, panel C shows this effect to be substantial. If the distance to the HD would drop from .5 km to 0 km (a twin-location), the propensity of combined shopping with Lidl would go up by no less than 37% for both Albert Heijn and Jumbo, without jeopardizing the incumbent's MSS or overall patronage propensity.

Robustness checks. As a robustness check, several alternative models are estimated. First, to check whether our model fully captures the effect of HD entry, we test a more flexible specification in which we allow the entry to directly impact on the shopping pattern and trip organization decisions, over and above the effect captured by the inclusive values. We do so by incorporating additional step dummies for HD entry in model layers A and B.[9] We find that these extensions do not lead to an improvement in model fit (i.e. AIC and BIC). Second, we estimate a model including loyalty (i.e. the fraction of trips in the previous month on which a chain was visited, see Briesch et al. 2009 for a similar measure) as an extra component of chain utility. This model points to only one segment of households and, as expected, leads to a much less pronounced effect for the other (in-store, basket and travel) utility components – suggesting that, indeed, their impact is reflected to a large extent in previous months' choices. As store introductions influence buying behavior through the same underlying factors (cf. Figure 2.1), this also reduces the model's ability to explain HD entry effects. Still, even in this model, complementarity significantly enhances the utility of both separate and combined multiple-store visits. In all, this lends further support to our findings.

[9] Specifically, we tested the following: (i) whether the choice between single-store and multiple-store patterns was directly affected by HD entry in general, and 'first-mover entries' (outlets that are the first HD to open in a local market) in particular, (ii) whether the choice between separate-trip and combined-trip patterns was directly affected by HD entry in general, and 'twin-location entries' (HD outlets that open up next to another grocery store) in particular. Details can be obtained from the authors.

2.6 Implications

While the parameters in Table 2.6, and the ensuing effects in Table 2.7, give a first feel for the drivers of HD entry losses, they do not yet paint the full picture. First, they do not document the magnitude of incumbent losses if a new HD enters the market. Second, they only point to partial (ceteris paribus) effects, whereas changes in the stores' offer or location will typically affect the stores' attractiveness in multiple ways. Below, we use the estimated parameters to simulate these implications, and analyze how they depend on the incumbent's competitive position vis-à-vis the HD – both geographically and in terms of complementarity. Next, we explore the effect of alternative marketing mix responses by traditional incumbents.

Consequences of local hard-discounter entry

To document the size and nature of incumbent losses, we first use the data across all households and local markets to quantify the HD entry effects. For each market, we consider the month prior to HD entry and use the model parameters, together with the conditions in that market (store locations and marketing mix variables), to calculate the households' patronage propensity and spending share for each local incumbent. We then compute these same quantities after bringing in the new HD entrant, keeping everything else constant, and compare the results.[10] We find that incumbents' average patronage losses range between 3.98% (Albert Heijn) and 12.52% (Edah), with an overall average of 8.33%. Spending losses, as expected, are somewhat lower, with an overall reduction of 7.85%, and average values for specific incumbents ranging between 3.45% (Albert Heijn) and 10.81% (Edah).[11] These

[10] By comparing predicted metrics of the two scenarios, we can control for marketing mix, and avoid a confounding with model forecast errors (see Chintagunta, Kadiyali and Vilcassim 2006 for a similar approach). To further enhance comparability and tractability, we did not include cases where HD entry coincided with entry or exit of another store.

[11] These figures are interesting in the light of a recent paper by Datta and Sudhir (2012). This study finds that the competitive impact of a store can be substantially driven by local zoning restrictions. However, given that HD's will seldom be the strongest player in a local market (in terms of market share), it is unlikely that their entry decisions were shaped by such restrictions.

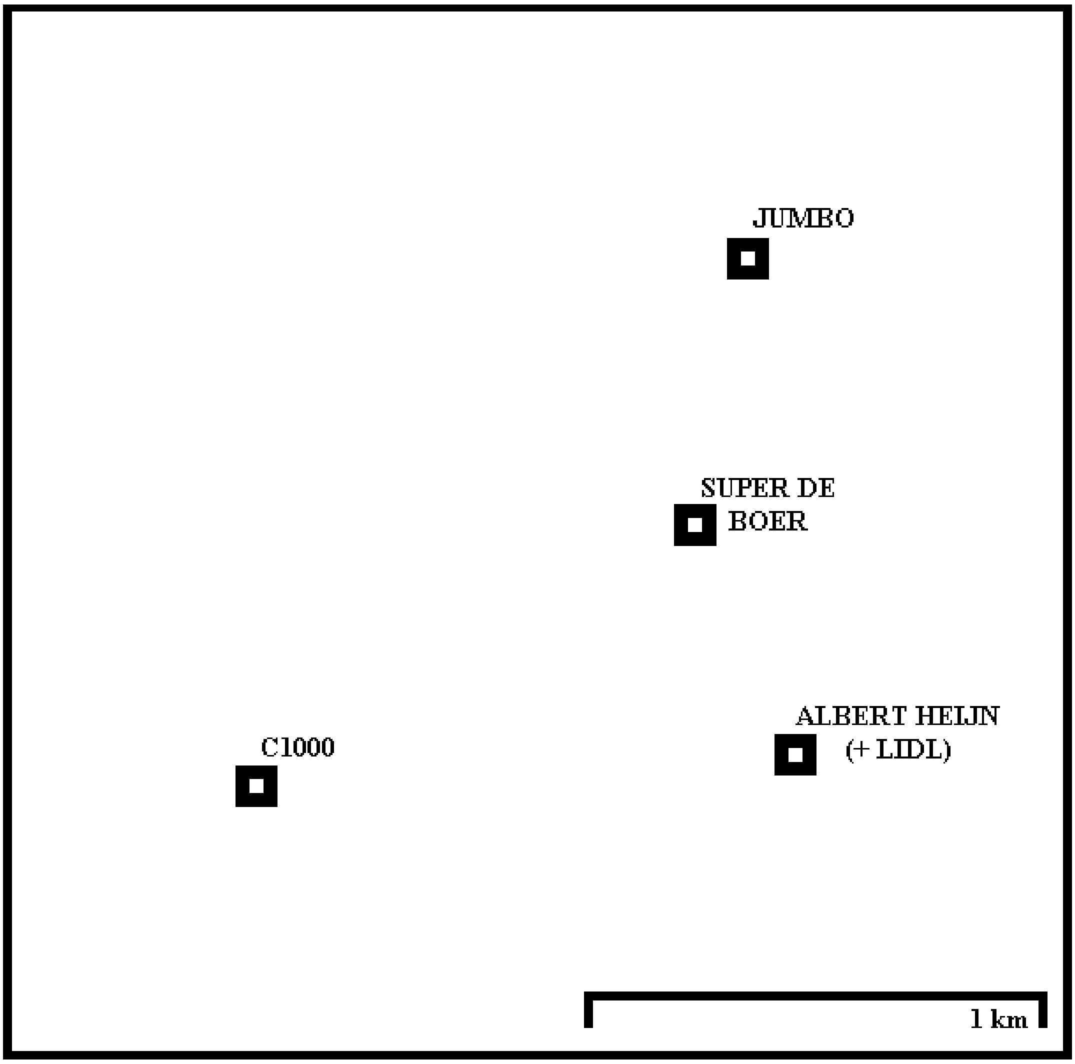
figures are sizable, but lower than those observed for large-discounter entry – which is not too surprising given that HDs cannot fully substitute for traditional supermarkets.

While these figures document the average losses that can be expected across a wide range of local market settings, the fact that they are average quantities makes it difficult to explain the differences observed between incumbent stores, and their underlying drivers. Losses may differ depending not only on the characteristics of a specific incumbent, but also on the presence and location of rival stores. To better disentangle these effects, we consider a local market (hereafter: market A) in which most of the incumbent chains (i.c. Albert Heijn, C1000, Jumbo and Super de Boer) operate only one outlet. This makes it easy to link changes in chain performance to the location of specific outlets. Figure 2.3 displays the relative geographical position of these outlets.

In January 2004, market A was confronted with the local entry of a Lidl outlet. Using our model parameters, we simulate the effect of the new Lidl outlet in twin-location with Albert Heijn – a strongly complementary traditional supermarket (average degree of complementarity in January 2004: .735). Again, we do so by comparing (i) incumbents' predicted performance for the month in which Lidl actually entered, with (ii) the predicted performance in the absence of Lidl's outlet – keeping all other factors constant. Given the role of distance in consumers' shopping behavior, the consequences of the HD opening will vary by household location. Therefore, we consider all possible household locations, i.e. for each unique 4-digit zip code in market A, we identify a geographical "center point" that will represent households in that zip code. Pre- and post-entry performance is then simulated for each of these center points,[12] and weighed with the number of resident households in the zip code (data source: Statistics Netherlands), before aggregating to the local market level. The implications are reported below.

[12] For all center points, we set category weights equal to the average across our sample.

FIGURE 2.3
Market A: Geographical Location of Outlets



Changes in store patronage. Table 2.8, panel A, reports the expected number of resident households visiting each incumbent before and after the HD entry. It also displays the fraction accounted for by single- and multiple-store (separate- or combined-trip) shopping.

The new Lidl outlet attracts a sizeable clientele (2,560 out of 9,425 households). As expected, only a small fraction of these Lidl customers (7.94%) engage in single-store shopping. Most of the HD shoppers opt for MSS on combined (25.7%) or separate trips (66.38%). The ensuing customer losses for incumbents vary widely, ranging from a low 6.1%

TABLE 2.8
Shifts in Patronage, Shopping Patterns and Spending in Market A as Result of Lidl's Entry

PANEL A: SHIFTS IN CHAIN PATRONAGE AND SHOPPING PATTERN DISTRIBUTION

	Before opening				After opening				Absolute change			Relative change		
Albert Heijn	3,781[a]	**S**[b]	1328	(35.1%)	3,549	**S**	1294	(36.4%)	-232	**S**[b]	-34	-6.14%	**S**[b]	-2.6%
		MS	2076	(54.9%)		**MS**	1901	(53.6%)		**MS**	-175		**MS**	-8.4%
		MC	377	(10.0%)		**MC**	354	(10.0%)		**MC**	-23		**MC**	-6.1%
C1000	4,451	**S**	1639	(36.8%)	3,848	**S**	1536	(39.9%)	-603	**S**	-103	-13.55%	**S**	-6.3%
		MS	2339	(52.6%)		**MS**	1935	(50.3%)		**MS**	-404		**MS**	-17.3%
		MC	473	(10.6%)		**MC**	377	(9.8%)		**MC**	-96		**MC**	-20.3%
Jumbo	3,837	**S**	464	(12.1%)	2,862	**S**	372	(13.0%)	-975	**S**	-92	-25.41%	**S**	-19.8%
		MS	2740	(71.4%)		**MS**	2029	(70.9%)		**MS**	-711		**MS**	-25.9%
		MC	633	(16.5%)		**MC**	460	(16.1%)		**MC**	-173		**MC**	-27.3%
Lidl	0				2,560	**S**	160	(6.3%)	+2,560	**S**	+160			
						MS	1922	(75.1%)		**MS**	+1922			
						MC	479	(18.7%)		**MC**	+479			
Super de Boer	2,767	**S**	584	(21.1%)	2,127	**S**	541	(25.4%)	-640	**S**	-43	-23.13%	**S**	-7.4%
		MS	1794	(64.8%)		**MS**	1316	(61.9%)		**MS**	-478		**MS**	-26.6%
		MC	389	(14.1%)		**MC**	270	(12.7%)		**MC**	-119		**MC**	-30.6%

PANEL B: SHIFTS IN CONSUMER SPENDING SHARE

	Before opening	After opening	Absolute change	Relative change
Albert Heijn	.275	.260	-.015	-5.5%
C1000	.324	.286	-.038	-11.7%
Jumbo	.225	.169	-.056	-24.9%
Lidl		.145	+.145	
Super de Boer	.176	.140	-.036	-20.5%

[a] Expected number of visiting households.
[b] Shopping pattern distribution: S=% of households visiting the chain in a single-store pattern, MS=% of households visiting the chain in a multiple-store separate-trip pattern, MC=% of households visiting the chain in a multiple-store combined-trip pattern.

(Albert Heijn) up to 23.1% and 25.4% (Super de Boer and Jumbo). Zooming in on the shopping patterns before and after entry, we find that incumbents mostly retain their single-store shoppers, losses among these customers being far below the overall drop in customer count (e.g. for Albert Heijn: 2.6% compared to 6.1%, for Super de Boer: 7.3% compared to 23.1%). As discussed in the conceptual part, this indicates that after HD entry, traditional chains' best customers generally keep shopping at these chains, and are thus not (completely) lost to the new entrant. From Table 2.8, it seems that especially upscale chains (like Albert Heijn) appear able to retain their loyal customers.

While the overall percentage of MSS slightly increases following entry (from 57.4 to 58.6%), most of the new HD shoppers already patronized multiple stores, and now trade one of the traditional chains for the HD entrant. Again, it seems that some chains are better able to stand their ground than others, and are less likely to be removed from the shoppers' choice set. Albert Heijn, for instance, succeeds in limiting the customer loss to 8.4% and 9.5% of its separate-trip and combined-trip shoppers respectively, while Super de Boer loses over 30% of its combined-trip shoppers. We will come back to these differences in vulnerability below.

Implications for spending. Next, we use our estimated spending-share parameters to predict, for each possible shopping pattern in market A, how households' monthly spending is allocated between the chains in that pattern. Combined with the simulated shopping-pattern probabilities, this indicates how Lidl's entry affects the spending at incumbents in market A. Table 2.8, panel B, displays the results. Not surprisingly, given its small proportion of single-store shoppers, the new entrant's spending share (14.5%) is far lower than its share-of-customers (27.2%). As for the traditional chains: we expected them to lose (relatively) less in terms of spending than in terms of patronage. Our simulation results are in line with this premise. Albert Heijn loses 5.5% in spending and 6.1% in patronage, while Super De Boer loses 20.5% in spending and 23.1% in patronage.

Role of store complementarity: Table 2.8 points to substantial differences in total losses among incumbent chains, the largest losses being experienced by incumbents that drop out of the multiple-store shoppers' choice set and are replaced by the new Lidl store. Why, then, do consumers abandon some chains, while they continue to visit others? As discussed earlier, our model estimates already revealed that stores with a complementary offer are more likely to be selected as the "store-set-of-choice" by multiple-store shoppers. Consistent with this, chains that exhibit the highest complementarity with Lidl (on average for Albert Heijn: .697, for C1000: .740, see Table 2.5) appear the least harmed, their losses in customer count and spending ranging between 5 and 14%, while less complementary chains such as Jumbo and Super de Boer face average customer and spending losses of 20 to 25%. Still, considering the large difference between Albert Heijn and C1000, other factors must also be at play.

Effect of store distance: An interesting observation from Table 2.8, panel A, is that the chain in twin-location with Lidl (i.e. Albert Heijn), suffers the least from its entry, and far less than the other complementary C1000-chain. As outlined in the conceptual part, a possible explanation is that its complementarity and co-location with Lidl make for an appealing one-stop shopping location. Customers that visited Albert Heijn along with a traditional incumbent, may now shift to the Albert Heijn-Lidl combination. To further investigate the role of distance, we simulate the effect of alternative entry locations on Albert Heijn. Specifically, we compare our original results (Lidl opening at the same location as Albert Heijn) with two alternative scenarios, in which Lidl locates at an intermediate distance (at .59 km away from Albert Heijn), or farther away (1.15 km distance from Albert Heijn). Interestingly, we obtain an inverted-U effect: Albert Heijn loses more if Lidl locates at an intermediate distance (7.0% patronage loss and 6.2% spending loss, compared to 6.1% and 5.5% for the twin-location), but losses become smaller again when the Lidl outlet is farther away (6.4% and 5.7% reduction in patronage and spending, respectively). Unlike earlier findings in the context of large-discounter entry, this suggests that if a traditional chain is more closely located to a HD entrant, this does not necessarily imply larger losses for that incumbent. Instead, local HD entry mainly hurts chains at a moderate distance: these players being too close to avoid competition for the same households, yet not close enough to form a one-stop shopping location with the HD.

To check the robustness of the findings, we also simulated the HD entry implications and incumbent responses in another local market, and obtained the same pattern of results. We do not report these for reasons of space – details can be obtained from the authors.

Response to hard-discounter outlet openings

Given that HD entry may entail substantial losses in customer count and spending, the question is how incumbents can mitigate these losses. Available reaction strategies differ in (i) the marketing mix instruments that are changed (i.e. a price drop, assortment increase, or change in PL share), and (ii) the product categories in which these changes are implemented. To get a feel for the effectiveness of alternative strategies, we return to the example of market A, where Super De Boer incurred huge losses following the entry by Lidl, and explore different options for Super De Boer to regain some of its customers and spending.

We note that proper response strategies will differ between (i) the traditional single-store shopping perspective (the upper part of Figure 2.1), in which the store’s actions influence its own attractiveness only, and (ii) our proposed multiple-store shopping perspective (lower part of Figure 2.1) in which the store’s actions also shape the appeal of the store sets of which it is part. With single-store shopping only, any “recovery” in patronage and spending should result from an increase in the chain’s own basket utility. We therefore start by calculating the changes in category price, assortment size and PL share that would be required to enhance Super de Boer’s list attraction by 1%. Since PLs also come with lower prices – on average 30% below those of the premium brands – we implement changes in PL share along with the corresponding reduction in category prices. We do so for two large product categories (meat and cheese, each capturing about 8% of consumers' share-of-wallet), and two smaller ones (prepared meals and diapers, each capturing 1.5%). Moreover, two of these products – meat and prepared meals – are "strong" categories, where Super de Boer has a higher category attraction than the HD, while the remaining two categories – cheese and diapers – are "weak" categories for the traditional chain.

Table 2.9, panel A, reports the results. It reveals that PL-share increases are not very effective, unrealistically high adjustments (ranging between +41.7% and +159.6%) being required to generate the desired increase in list attraction. This can be explained by the fact that the positive price reduction effect of a higher PL share, almost cancels out against the negative "brand equity" effect. The table shows that price tends to be an "efficient" instrument in categories where the traditional chain is weaker than the HD (e.g. cheese), while assortment increases are more efficient in categories where it is stronger (e.g. meals). This makes intuitive sense, since traditional chains are typically weak in price-sensitive categories, and strong in categories where assortment variety is key. It also shows that the appropriateness of marketing mix actions (e.g. price cuts, assortment extensions) as response mechanisms is highly category-specific. When consumers visit only one store, price and assortment changes that yield the same change in list attraction will also have the same effect on customer counts and spending (see also the elasticity expressions in Appendix 3). In such a single-store shopping setting, each of the actions in Table 2.9, panel A would generate the same performance recovery. That is, making abstraction of cost differences, Super de Boer would be indifferent between, say, a .73% reduction in the price of cheese, and a 4.45% increase of its meat assortment. However, the picture becomes different when multiple-store shopping and the underlying role of store complementarities are accounted for (the lower part of Figure 2.1), as is the case in our model. This is clear from Table 2.9, panel B, which shows the shifts in patronage patterns brought about by the different response strategies. Even though they entail equivalent increases in list attraction, changes in strong categories lead to a strikingly different recovery pattern than changes in weak categories. Specifically, while improvements in strong categories entail a similar recovery of single-store shoppers for Super de Boer (+9.58% points for meat and meals, compared to +9.71% points for cheese and +9.50% points for diapers), they allow the chain to "haul back in" far more customers who start shopping at both Lidl and Super De Boer (+8.03% and +7.99% points for meat and meals, only +2.09% points and +1.04% point for cheese and diapers). The reason is clear: unlike remedying its weak points, further improving on its strong points enhances Super de Boer's complementarity with Lidl (in our example: from .536 to .555), which, in turn, increases the appeal of the Super de Boer-Lidl store set.

TABLE 2.9
Impact of Alternative Response Strategies for Super de Boer (SdB)

	Categories where SdB is strong		***Categories where SdB is weak***	
	Meat	Prepared meals	Cheese	Diapers
PANEL A: CHANGE IN MARKETING INSTRUMENT IN CATEGORY AT SUPER DE BOER				
Price	-10.13%	-15.23%	-.73%	-17.77%
Assortment	+4.45%	+25.44%	+2.55%	+70.99%
PL share	+159.57%	+108.43%	+41.70%	+141.96%
Change in SdB's list attraction	+1.00%	+1.00%	+1.00%	+1.00%
PANEL B: IMPACT ON PATRONAGE AND SPENDING				
Change in fraction of customers in shopping pattern (in % points):				
SSS Lidl	-.26%	-.26%	-.21%	-.24%
MSS Lidl+competitor	-10.22%	-10.47%	-4.33%	-11.57%
MSS Lidl+SdB	+8.03%	+7.99%	+2.09%	+1.04%
SSS SdB	+9.58%	+9.58%	+9.71%	+9.50%
MSS SdB+competitor	+14.09%	+14.63%	+8.49%	+30.18%
Any pattern Lidl	-2.45%	-2.74%	-2.45%	-10.77%
Any pattern SdB	+31.70%	+32.20%	+20.29%	+40.72%
Overall Patronage:				
Lidl	-.09%	-.11%	-.09%	-.40%
SdB	1.53%	1.56%	+.98%	1.97%
Overall Spending:				
Lidl	-.10%	-.11%	-.10%	-.40%
SdB	1.62%	1.64%	1.18%	1.96%

Interestingly, this "complementarity-enhancing" strategy may also reveal less detrimental to Lidl, as can be seen from Table 2.9. Improvements for meals (a category where Super de Boer is strong) lead to a smaller customer loss for Lidl than comparable improvements for diapers (a category where Super de Boer is weak instead) (-.11%, compared to -.40%). Hence, this strategy may allow the incumbent to recover defected customers while keeping the risks of a counterattack from the HD low. In some cases, it even leads to better results for Super de Boer overall. For instance: marketing-mix improvements in the (strong) meat category imply a 1.53% (1.62%) recovery in the number of customers (spending), compared to only .98% (1.18%) for the (weak) cheese category.

2.7 Discussion

In this paper, we address the impact for traditional supermarkets, of local entry of a hard-discounter – a store format that has invaded Europe and is strongly on the rise in the US. Building on the literature on multiple-store shopping, we propose a framework in which consumers can respond to HD entry along multiple routes, taking into account the complementarities between the entrant and traditional incumbents. We test this framework using a unique panel data set covering over 190 local HD entries in the Netherlands. In so doing, we shed light on the size and nature of the losses incurred by incumbent supermarkets as well as the drivers of these effects, and explore how traditional chains can mitigate the harmful consequences of these "close encounters with the hard-discounters".

Our main substantive findings are as follows. Like large-discounter entry, the advent of a hard-discounter store can lead to substantial losses for incumbents. Interestingly, however, the underlying pattern of consumer reactions and the drivers thereof, are substantially different. Specifically, we identify four major aspects in which HD entry effects differ from large-discounter entries.

First, unlike large-discounter entry, which "makes the incumbent chain lose some of its best customers" (Singh et al. 2006, p. 475), entry of a HD hardly affects traditional supermarkets' loyal customer count. Customers defecting to the HD are mainly those who already patronized multiple stores, and now trade in one of the incumbents for the HD chain.

Second, in contrast to what was observed for large-discounter entry, the largest source of incumbent losses comes from a reduction in the number of store customers rather than a reduction in average spending. Losses in spending remain more limited, as they are mainly incurred on customers that spent only a portion of their wallet at the chain.

Third, the type of incumbent most strongly hurt is also quite different. Large-discounter entry revealed particularly troublesome for chains with strong assortment overlap, i.e. chains operating in the same product categories as Wal-Mart (Ailawadi et al. 2010, Gielens et al. 2008). In contrast, our results indicate (i) that supermarkets and HDs can carry the same categories but still be complementary in their price/assortment emphasis for these categories, and (ii) that such complementarity reduces incumbents' losses. By spreading their outlay across the traditional supermarket and the HD, consumers can "pick the best of both worlds". It follows that especially upscale supermarkets, which derive their strength from carrying varied assortments with well-known brands, may be in better shape to withstand HD entry. On the one hand, their loyal clientele of single-store shoppers is unlikely to defect to the HD. On the other hand, multiple-store shoppers interested in the HD, are likely to visit it alongside a complementary chain (i.c. the upscale incumbent) that serves their needs in categories where they want "the best of the best" (Nielsen 2008).

Fourth, we obtain interesting effects of location. Opposite to the findings for large-discounter entry (Ailawadi et al. 2010, Singh et al. 2006), our results show that being closer to the new HD may mitigate losses. Becoming part of a twin-location with the HD may turn the traditional supermarket into an attractive option for chained visits, enabling it to better compete with rival stand-alone chains serving more distant locations. However, this only works for supermarkets in close proximity to the entrant, resulting in an inverted U-shape distance effect: HDs locating at mid-range distance being more harmful than those opening up right next to, or farther away from, the incumbent.

From a managerial perspective, we provide new insights for retailers in search for a suited response to local HD entry. Recommended reactions to large-discounter entry include minimizing assortment overlap and setting more competitive prices across-the-board (e.g. Ailawadi et al. 2010, Gielens et al. 2008). Faced with intensified HD competition, however, incumbent responses may have to be differentiated across product categories. Indeed, the bigger losses occur because consumers trade one incumbent in their store set for the HD, and keep on visiting the (other) incumbent most complementary with the HD. It follows that to mitigate losses, incumbents should not just focus on enhancing their own basket utility, but should also consider how complementarity with the HD is affected. We show that, by improving in categories where it is strong (and the hard-discounter is weak), an incumbent can form an appealing store set with this HD, and haul back in multiple-store shoppers while lowering the risk of a counterattack of the HD.

2.8 Limitations and Future Research

Clearly, our study has a number of limitations, and opens up new research opportunities. First, given our focus on multiple-store shopping as a driver of HD entry effects, we modeled changes in households' systematic shopping patterns. While we document how many customers stay as regular shoppers and what proportion of their outlay is spent at the incumbent store, we neither shed light on the specific number of visits to the incumbent store nor on the possible changes in total grocery spending following HD entry. Second, our study underscores the importance of store complementarity, which results from cross-category differences in consumers' sensitivity to price, assortment and quality. While we operationalized these complementarities based on "average" marketing mix sensitivities (to keep the number of parameters in check) – and already uncovered a highly significant effect, future studies may further accommodate household heterogeneity in marketing-mix responsiveness within these different categories. Third, though fostering complementarity is an appealing option for incumbents in the immediate vicinity of the HD, supermarkets located at mid-distance from the new HD may not enjoy any agglomeration effects, and may need to take a defensive stand. While we considered straight price cuts and standard-private label share increases, an alternative approach for supermarkets may be the introduction of a dedicated, low-priced private label line. The jury is still out on whether this allows them to (profitably) recover customers and customer spending – a topic worth pursuing. Fourth, our findings corroborate the importance of a "category-management" approach, in which price and assortment reactions are attuned to local competition on a category-by-category basis. Yet, we could not generate guidelines on the optimal price shifts or assortment changes, which would also require insights into the costs involved in these strategies. Moreover, the best-suited response may also depend on the offer and location of other incumbent supermarkets – issues that we leave for future study. Finally, our current dataset covers multiple local Dutch markets, each with its own unique competitive setting (in terms of the chains that are present, and the location of these chains relative to consumers and each other). Still, it would be interesting to conduct this study for other countries as well, so as to replicate our analysis for an even larger number of different market configurations. An intriguing question, for instance, is how advent of a HD would re-shape competition in a market where a large-discounter (a format not found in the Netherlands) is already present. Will the HD not survive such competition? Or would it, by "teaming up" with traditional chains, actually help those chains stand up against the giant? These are fascinating issues for future research.

Chapter 3 Battling for the Household's Category Buck: Can Economy Private Labels Help Defend Against the Hard-Discounter Threat?

3.1 Introduction

Hard-discounters (HDs) – with Aldi and Lidl as prime exemplars – have been dramatically on the rise. By streamlining their operations and economizing on assortment and in-store service, these chains can offer grocery merchandise at rock-bottom prices (Steenkamp and Kumar 2009). This has helped HDs in conquering the "hearts and minds" of a growing segment of consumers, who believe them to provide better value-for-money than "traditional" formats (Business Insights 2008). As such, HDs have made major inroads into the trade of these traditional supermarkets, capturing up to 35% of market share in some countries (Cleeren et al. 2010) and causing sales losses of up to half a trillion dollars per year (Steenkamp and Kumar 2009).

In the face of this threat, traditional retailers have found themselves forced to develop appropriate "defense" strategies against these HDs. While these strategies may revolve around a further differentiation of the store (e.g. assortment extensions or improvements in customer service) (Cleeren et al. 2010), most retailers opt for a more head-on approach that reduces the price gap with the HD. Traditional chains have, for instance, been found to substantially cut their product prices (Van Heerde et al. 2008), or launch a discount subsidiary of their own (Cleeren et al. 2010).

An alternative price-related response to the HD threat is the introduction of a dedicated "budget" or "economy" private label line (Ailawadi et al. 2008). This line comprises very basic "no-frills" products, sold for a bargain price – and, as such, is intended to provide an alternative to the products sold at HDs (Dekimpe et al. 2011). While somewhat similar to the cheap "white label generics" that were popular in the 1970s and 1980s (Dick, Jain and Richardson 1995; Neidell, Boone and Cagley 1984; Szymanski and Busch 1987), economy private labels (EPLs hereafter) nowadays are much more central to retailers' private label strategies, and are usually carried alongside a "standard" and/or "premium" private label tier (Geyskens et al. 2010). EPLs have become an increasingly common sight, as many top European retailers like Asda (UK), Carrefour (France) and Migros (Switzerland) have introduced them in response to the growing HD presence (Coriolis Research 2002; Just-Food 2006; Steenkamp and Kumar 2009).

From an academic perspective, however, not much is known about whether EPLs are actually effective in "fending off" the HD threat. Available research on EPLs is primarily carried out at the brand level – focusing on how EPLs affect the share of other (store) brands within the retailer's assortment (e.g. Geyskens et al. 2010) – and therefore does not reveal their potential as a defense mechanism against HDs. Such knowledge, though, would be particularly interesting in the light of a recent study by Hansen and Singh (2008), who find that a higher share of standard private label products may actually foster (rather than prevent) consumer switching to a large-discounter (i.c. Wal-Mart). Whether EPLs may have a similar counter-productive effect on competition from the HD is however uncertain, because of two major differences in competitive situation. First, EPLs provide a much larger price advantage (than standard private labels), and a better matching point vis-à-vis HDs (Business Insights 2008). While this lower price may enhance consumer price sensitivity even further (Chintagunta, Bonfrer and Song 2002) – and as such trigger extra shifts in spending towards discounters – it may also produce the opposite effect. Second, HDs constitute an entirely different business model from large-discounters (as is explained in chapter 2 of this dissertation). In contrast to large-discounters, whose wide and deep assortments make for a full-fledged alternative to traditional chains, the HD's attractiveness – and thus its impact of entry – may strongly vary across categories (Nielsen 2007). While this makes the need for an appropriate "defense mechanism" against HDs more pressing in some categories than others, it likely causes the ability of EPLs to fulfill this role to be category-specific as well.

Taken together, this leads to the following research questions. First, when a HD enters a (traditional) retailer's trading zone, what portion of customers' purchases will be lost across different categories? Second, do EPLs act as a defense mechanism, that is, are category sales losses lower if an EPL is available in the category prior to HD entry? Third, can we identify category characteristics that influence the seriousness of the HD threat and/or the power of EPLs to shield against this threat? We will answer these questions by using a difference-in-difference approach, which allows us to infer the impact of HD entry by comparing pre- and post-entry category sales – both in the absence and presence of EPLs. Because EPL presence is not exogenous, this difference-in-difference approach will be combined with a selection model to correct for endogeneity bias.

From an academic perspective, our study contributes to the literature on store format competition and category-specific store loyalty, and fits into Ailawadi and Keller (2004)'s call for more research on how differently positioned private labels (such as EPLs) affect a retailer's performance. For retailers, we shed light on the power of EPLs in keeping HDs at bay, and offer guidance on what categories these low-tier brands should primarily be offered in. Such insights are particularly compelling given that many retailers are still in the process of rolling out their EPL program across product categories.

The remainder of the paper is structured as follows. In the next section, we characterize EPLs, and give a theoretical rationale for why carrying this tier of private labels may or may not prevent store customers from shifting their purchases to HDs. We then describe our modeling approach, followed by the empirical setting and data. Next, we present the estimation results, and provide a discussion of these findings. The last section indicates limitations and offers directions for further research.

3.2 Theoretical Background

Economy private labels are carried by an increasing number of retailers as part of a "multi-tiered" private label strategy. Their prices are very low: on average 50 to 60% below those of the leading national brands within a category, and 40 to 50% below standard private label prices (Nauwelaers et al. 2012). However, their quality tends to be lower than that of national brands as well, as EPLs are often manufactured using cheaper ingredients and/or dated production technologies. In addition, EPL products only come in a few varieties per product category, generally have a sober packaging, and receive limited or no marketing support (Business Insights 2008; Geyskens et al. 2010; Kumar and Steenkamp 2007). Unlike standard private labels, which are typically positioned as "similar quality to national brands at a lower price" (Kumar and Steenkamp 2007), EPLs are usually marketed as "basic, no-frills products at rock-bottom prices".

Whereas standard private labels are geared towards competition with national brands (Kumar and Steenkamp 2007), retailers often introduce an EPL to defend against the "hard-discounter threat" (Geyskens et al. 2010). Several arguments can be made for why such an approach could prove effective. First, the price advantage of EPLs over leading national brands is in general on par with that of HD products; in some cases, it is even larger (Business Insights 2008). Unlike standard private labels, EPLs thus help traditional retailers to match or even beat the prices found at their HD competitors. Second, and somewhat related, carrying EPLs allows traditional supermarkets to better cater to consumers' "dual demand" – a term recently coined by Nielsen (2008) to denote consumers' desire for superior quality in some instances, alongside a focus on savings in others. By adding an EPL to his regular assortment of renowned national brands and standard private labels, a traditional retailer can cover the full range of consumer needs – providing customers with a "best of the best" product alternative in terms of quality as well as in terms of price. This makes it less likely that consumers will purchase (a large) part of their basket at a second store – possibly the HD – to satisfy those multi-faceted needs (Gijsbrechts et al. 2008). Third, since EPLs (similar to standard private labels) are in general exclusive to a specific retailer, they may help that retailer to further differentiate from its competitors. This, in turn, may increase store switching costs and foster store loyalty – preventing consumers from shifting part of their purchases to a (HD) competitor (e.g. Ailawadi, Neslin and Gedenk 2001; Corstjens and Lal 2000; Sudhir and Talukdar 2004).

While the above arguments suggest that EPLs are an effective way for a retailer to defend himself against HDs, the current marketing literature provides counter-arguments as well. To start off, empirical support for the above store loyalty argument has been far from unequivocal. Pauwels and Srinivasan (2004), for example, do not observe systematic improvements in store traffic after retailers add a private label to their assortments. Other scholars indicate that only specific types of private labels will be able to build store loyalty. Private labels need to be of high quality, and their packaging should be at least somewhat distinctive before they can serve as a means to differentiate a store (Corstjens and Lal 2000; Dick et al. 1995). In contrast, a strong focus on price advantages only tends to lead to "private-label proneness" – with consumers developing a preference for (low-priced) private labels in general, rather than for a specific private label and the store that carries it (Dawes and Nenycz-Thiel 2012). This perspective seems to cast doubt on whether EPLs – with their extremely low price, basic quality and sober packaging – can make customers more store loyal, and less prone to switch to a HD.

Moreover, while EPLs are generally just as cheap as products sold at HDs, they may still compare unfavorably when it comes to product quality. EPLs offer a quality that is "basic and acceptable" (Geyskens et al. 2010). In contrast, HDs (whose lower prices stem from streamlined operations and lean assortments, rather than low-cost production processes) sell products that can easily match the quality of top national brands – as has often been demonstrated by consumer organizations and testing agencies (Steenkamp and Kumar 2009). Besides objective quality, EPLs may also be at a disadvantage regarding perceived quality, as their minimalistic packaging and limited marketing support are likely to keep consumers' quality expectations low (Moorthy and Zhao 2000; Richardson, Dick and Jain 1994). In sum, EPLs are unlikely to serve as a perfect substitute for HD products in terms of quality. This, again, calls their propensity to shield against HDs into question.

Finally, some studies suggest that EPLs may even be "counterproductive" in this regard, and may motivate customers to switch to a HD store. The primary argument here is that the introduction of a (low-priced) private label can render price differences more salient and increase consumers' price sensitivity (Chintagunta et al. 2002; Pauwels and Srinivasan 2004). This makes consumers more susceptible to the HD, as it offers products comparable in quality to national brands, but at a much lower price. This notion is supported by Ailawadi et al. (2008) and Hansen and Singh (2008), who find private label buyers to be more prone to buy from discounters as well. While these authors studied private labels in general, their findings may particularly apply to lower-quality private labels (like EPLs), which especially "emphasize and intensify consumer price sensitivity" (Corstjens and Lal 2000).

In sum, while several theoretical and practical arguments can be made for why EPLs constitute an effective defense tool against HDs, other arguments point in the opposite direction. The net outcome of these forces, therefore, remains an empirical issue. Moreover, this effect may very well differ between product categories, depending on their intrinsic characteristics and on the HD's category-specific offer. Indeed, consumers' proneness to buy at a given store format has been shown to differ across categories (e.g. Bell et al. 1998; Inman et al. 2004). In addition, inter-category differences are found to be a strong driver of (standard) private label power (e.g. Dawes and Nenycz-Thiel 2012; Dhar and Hoch 1997; Hoch and Banerji 1993; Steenkamp and Dekimpe 1997). This may also apply to EPLs – and their effectiveness vis-à-vis HDs. To gain more insights into the actual power of EPLs as a defensive tool, we thus need to empirically assess (i) the extent to which traditional retailers' category sales are affected by HDs, (ii) the moderating role of EPLs therein and (iii) whether these effects differ across categories. Below, we present a methodology that allows us to address these issues.

3.3 Methodology

As indicated above, we need to single out how the presence of an EPL in a product category affects a traditional retailer's sales losses in that category upon HD entry. This poses several methodological challenges.

First, we need to separate the category sales losses triggered by HD entry, from other sources of variation in sales. We achieve this through a before-after approach, in which we use the market entry of HD outlets as a natural experiment. Specifically, we consider trading zones or "local markets" in which a HD outlet opened up in the course of our observation period. For each traditional store in those markets, we then compare category sales in the period before the HD store enters, with sales in the same period post-entry, and use this as the dependent variable in our model. To reduce the effect of other over-time changes, we keep this period rather short (four months before and after HD entry). At the same time, to rule out that the sales shifts are caused by differences in the composition of the customer base, rather than by the defection of given customers to the HD, we calculate our dependent variable by household, and carry out the analysis at the household-level.

A second key challenge is to assess whether these category sales losses systematically differ with the presence or absence of an EPL. This calls for a "difference-in-difference" approach. One possibility would be to compare the entry losses for categories in which an EPL is present, with categories in which it is not. Such an approach is not feasible, however, for two reasons. For one, it would presume that, in the absence of an EPL, losses to HDs would be similar across categories. This is a highly unlikely assumption, given that HDs appear to be more successful in some categories than in others (Nielsen 2007). Moreover, it would ignore the possibility that categories in which an EPL is introduced are the ones where EPLs are more effective per se – resulting in an upward bias of its estimated effect. To resolve this issue, we exclusively focus on categories in which an EPL actually became available in the course of our data period. While such EPL launches are "national" and occur simultaneously for every local market where the traditional chain is active, this does not hold for the entry of HD outlets. Hence, for each product category, we have local markets where HD entry preceded the category's EPL launch, as well as markets where the category's EPL was introduced prior to HD entry. The variation over time in local HD entry therefore allows for within-category comparisons of the impact of HDs in the presence or absence of an EPL.

Third, focusing exclusively on categories in which an EPL was introduced may create a selection problem, which we resolve using the traditional Heckman procedure (Heckman 1979; see the empirical section for details). Fourth, given that a store's clientele may differ across local markets (Campo et al. 2000) and that between these local markets, consumers may differ in their reactions, we need to control for household and local-market characteristics. Fifth, even with a rather contained period, part of the difference between pre- and post-entry sales may result from contemporaneous changes in the traditional retailer's own marketing mix, rather than from the HD's entry. Again, our model needs to explicitly control for such effects.

Last but not least, we must allow the losses from HD entry, as well as the moderating effect of EPL presence on these losses, to differ across categories. To this end, we adopt a latent class approach: we estimate the model simultaneously across categories, but allow the key parameters to differ between latent groups of categories. This leads to the following specification for the main model:

[3.1] $\Delta PQ_{h,c,k} \left| s = \Delta PQ^{*}_{h,c,k} \right| s + \varepsilon_{h,c,k}$, where:

$$\Delta PQ^{*}_{h,c,k} \Big| s = \beta_{0,s} + \sum_{k=1}^{K-1} \beta_{1,k,s} + \beta_{2,s} * EPL_{h,c,k} + \psi * IM_{c} + \sum_{l} \delta_{l} * Z_{l,h} + \sum_{m} \lambda_{m} * \Delta X_{m,h,c,k}$$

Here, c denotes the product category, k indexes the traditional chain, h is a household indicator (note that since each household panel member resides in a particular local market, there is no need for a separate local market indicator) and s indexes the latent class (group) of categories. IM_c is the "inverse Mills ratio" of the Heckman procedure to correct for possible selection bias (see the next section for more details), Z is a vector with household- and other local-market control variables, and ΔX is a set of controls related to marketing mix changes concurrent with the opening of the HD outlet.

The dependent variable in equation [3.1] is based on household *h*'s average monthly purchase quantity in category c and traditional chain *k*. $\Delta PQ_{h,c,k}$ indicates the percentage difference in this amount before and after HD entry in household *h*'s local market.[13] As a result, the main intercept β_0 and chain-specific deviations $\beta_{1,1}$ to $\beta_{1,K-1}$ capture the sales impact

[13] Note that this approach implies that for each household/category/chain, we only use a single observation. This eliminates the need for a time subscript, even though these observations pertain to multiple periods in time.

of HD entry for K traditional chains (in the absence of an EPL).[14] $EPL_{h,c,k}$ is a dummy variable that indicates whether chain *k* offered an EPL in category *c* at the time of HD entry in household *h*'s local market. The corresponding parameter β_2 is our main parameter of interest. Its sign and significance will indicate whether carrying an EPL reduces – or amplifies – the impact of HD entry on traditional retailers. As can be seen from [3.1], we allow the EPL parameter β_2 as well as the (chain) intercepts β_0 and $\beta_{1,k}$ to vary over latent classes (i.c. category groups).[15] The corresponding log-likelihood function takes the following form:

$$[3.2] \quad \sum_{c=1}^{C} \ln \sum_{s=1}^{S} \varsigma_s \prod_{h}^{H_c} \prod_{k}^{K_{h,c}} \frac{1}{\sqrt{2\pi\sigma^2_{h,c,k}|s}} \exp\left\{-\frac{1}{2}\frac{(\Delta PQ_{h,c,k}|s - \Delta PQ^*_{h,c,k}|s)^2}{\sigma^2_{h,c,k}|s}\right\},$$

where ς_s is the size of latent class *s*, *S* is the best-fitting number of latent groups, H_c is the set of households that we observe in category *c* and $K_{h,c}$ is the set of traditional chains in which we observe purchases of category *c* by household *h*.

3.4 Data and Operationalizations

Data Sources and Research Setting

Our data comprise household scanner panel data for the Dutch market (provided by GfK), covering the period 2005-2006. This data pertains to a large number of product categories, as classified by GfK. The data set also contains information on socio-demographic characteristics of the households, along with their geographical location. For the same period, we have access to weekly outlet-level IRI data on the major Dutch supermarket chains,

[14] While our approach is to assess the defensive power of EPLs by comparing HD entry effects in presence versus absence of an EPL, one of the traditional chains in our data (Albert Heijn) already introduced their EPL ('Euroshopper') in the considered categories before our observation period started. Hence, we don't observe variation in EPL presence versus absence for this chain. In order to avoid confusion between the impact of EPL presence on the one hand, and the appeal of the Albert Heijn chain in the considered categories on the other, we will keep the EPL dummy fixed at zero for this chain. Hence, in the case of Albert Heijn, the intercept reflects category sales changes after HD entry, given that its EPL is already present.

[15] To incorporate additional flexibility in the model, we also allow the error variance to vary across classes.

including the zip codes for all outlets of these chains. Last but not least, we have information on the SKU listing dates for the EPL of Dutch chain Super de Boer ("Happy Euro").

As mentioned in the previous section, our model is specified in the context of local HD entry. We use the IRI data to identify these entries: by comparing week-to-week sales levels, we locate 45 outlets of HD chains Aldi and Lidl that opened up in 2005 or 2006.[16] These HD outlet openings will allow us to calculate the dependent variable (before-after entry difference in category spending at traditional chains) for every household that resides nearby one of these HD outlets (see also below).

Our SKU listing data set for Super de Boer's EPL indicates that while this line first emerged in 2003, it was introduced in the majority (89%) of categories between 2005 and 2006 (i.e. our observation period). Henceforth, we focus on those categories. Even within this two-year period, considerable variation exists in the exact timing of the EPL introduction across categories. This, together with the fact that the 45 HD entries are also spread in time, implies that for many categories we observe both (i) local markets in which the HD entered in the absence of an EPL, as well as (ii) local markets in which the EPL was already present at the time of entry. Specifically, an EPL was absent (present) in 38% (62%) of the observed category/entry-combinations, ensuring the feasibility of our "difference-in-difference" approach.

As for the households, we assume that they are only likely to respond to a local HD entry if it makes the format more accessible to them in terms of travel distance. This implies that we only consider those households for which one of the 45 HD entrants opened up at near distance from the household's home (i.e. within a 5 km radius, see Hwang et al. 2010) and

[16] In the same fashion, we identify outlet openings (and closures) of other (traditional) chains, data that will be used to calculate their distance from each household.

became the nearest HD outlet available.[17] Additionally, for each household, we only track its purchases in categories that were already bought before HD entry. Our final sample thus consists of 397 households, whose purchasing behavior is observed across 48 product categories. Table 3.1 provides an overview of the categories, along with information on the EPL introduction dates in these categories.

TABLE 3.1
Product Categories and Dates of EPL Introduction at Super de Boer

Product category	EPL introduction	Product category	EPL introduction
Air freshener	January 2006	Margarine	February 2006
Baking products	May 2006	Microwave meals	October 2005
Butter cakes	April 2006	Milk	November 2005
Bread	February 2006	Muesli	October 2005
Canned meat	December 2005	Mustard	March 2006
Canned vegetables	November 2005	Oils	January 2006
Cheese spread	December 2005	Pancake mix	February 2006
Coffee	May 2006	Pasta sauce	February 2006
Coffee creamer	March 2006	Peanuts and nuts	November 2005
Cold cuts	October 2005	Powder detergent	December 2005
Cookies	January 2006	Prepared meat	December 2005
Dry biscuits	January 2006	Rye bread	December 2005
Eggs	January 2006	Salad dressing	March 2006
Fabric softener	January 2006	Salads	November 2005
Fresh vegetables	November 2005	Sandwich salads	October 2005
Fruit compote	February 2006	Sausages	January 2006
Frying fat	January 2006	Shampoo	February 2006
Grated cheese	December 2005	Spaghetti	March 2006
Gravy products	April 2006	Sprinkles	February 2006
Hair gel	February 2006	Tea	January 2006
Hard cheese	December 2005	Toilet paper	November 2005
Jam	January 2006	Vermicelli	April 2006
Ketchup	February 2006	Vinegar	March 2006
Liquid detergent	December 2005	Waffles	November 2005

Though we will infer the defensive power of EPLs from our data for Super de Boer, we also include category sales shifts at three other chains (Albert Heijn, C1000 and Plus, who together with Super de Boer account for 48% of Dutch supermarket sales in 2005-2006). While no variation in EPL presence is observed for these chains (Albert Heijn's EPL was

[17] Only one household encountered more than one HD entry over the observation period. For that household, we considered the entry that was first to occur.

available throughout the entire observation period – see also footnote 14 – while C1000 and Plus did not carry an EPL at all), the rationale behind including these observations is twofold. First, the observations of other chains may allow for a more reliable assessment of the category-specific effects of HD entry, and of the controls – leading to a cleaner estimate of the EPL impact. Second, including data for these chains is interesting in its own right, as it sheds light on the HD losses for traditional supermarkets other than Super de Boer. In total, we thus have 6868 observations available for model estimation.[18]

Variables and Operationalizations

Dependent variable

The dependent variable in our model, $\Delta PQ_{h,c,k}$, is defined as the percentage difference in household *h*'s average purchase quantity (expressed in volume units, such as kilograms or liters) of category *c* in chain *k*, in the period before and after HD entry. We consider a four-month period, and average across months, so that the dependent variable is operationalized as follows (with $\phi(h)$ being the month in which the HD entered household *h*'s local market and *M* being equal to 4):

$$\Delta PQ_{h,c,k} = \frac{\frac{1}{M}\sum_{m=1}^{M} PQ_{h,c,k,\phi(h)+m} - \frac{1}{M}\sum_{m=1}^{M} PQ_{h,c,k,\phi(h)-m}}{\frac{1}{M}\sum_{m=1}^{M} PQ_{h,c,k,\phi(h)-m}}$$

$PQ_{h,c,k,t}$ is household *h*'s total purchase quantity of category *c* in chain *k* and in month *t*. Before we obtain these values from our panel data set, we first apply a correction for possible

[18] Note that: (i) each household/category/chain-combination is a single observation in our data set, (ii) some households buy a category in more than one chain, and (iii) not every category is bought by all households.

seasonality in category sales.[19] This ensures that we will not confuse differences in purchase behavior due to HD entry with those resulting from seasonal shifts.

Independent variables

To accommodate chain-specific fixed effects, our main model incorporates chain dummies for the major players (C1000, Plus and Super de Boer) except Albert Heijn, which serves as the reference chain. Hence, in equation [3.1], $\beta_{0,s}$ will capture the (category-group specific) sales loss from HD entry for Albert Heijn. For the remaining chains, this loss is given by $\beta_{0,s}$ plus their chain-specific deviation $\beta_{1,k,s}$. The EPL effect is captured by a step dummy, equal to 0 if, at the time of HD entry in a household's local market, the EPL was absent from the category in the chain, and equal to 1 if it was present. An alternative would be to measure the number of SKUs in the category's EPL line. However, given that this number hardly varies after the EPL is introduced (consistent with the observation that EPL lines comprise only few, basic SKUs), this operationalization would not add much.[20]

As for the household and local market controls, we include five household demographic variables ($HHsize_h$, $Children_h$, $Income_h$, $DualInc_h$ and Age_h) to proxy for household traits that may drive susceptibility to HD entry, such as time availability, taste variance and price sensitivity (for details on the measurement of these variables, see Table 3.2). In addition, we control for differences in households' local store environments by including two store distance variables. $\Delta DistHD_h$ is the change in household *h*'s travel

[19] To correct for seasonality, we proceed as follows. First, we compute monthly category sales totals from our panel data set, for the period 2002-2006. We convert these monthly sales into 'indices' by computing their percentage deviation from the category average. For each category, we then regress these indices on month dummies. The coefficients of these regressions may be interpreted as the month-to-month (percentage) deviations from the category's average sales level. We subsequently apply these coefficients to the sampled households' purchase quantity averages to obtain the deviations at the household level. As a final step, we subtract these deviations from households' actual monthly purchase quantities.

[20] We estimated a model in which the step dummy was replaced by the number of EPL SKUs, and found the pattern of results to remain the same.

TABLE 3.2
Variable Operationalizations (Main Model)

Notation	Variable name	Operationalization
Dependent variable		
$\Delta PQ_{h,c,k}$	*% change in category purchase quantity*	$\dfrac{\frac{1}{M}\sum_{m=1}^{M} PQ_{h,c,k,\phi(h)+m} - \frac{1}{M}\sum_{m=1}^{M} PQ_{h,c,k,\phi(h)-m}}{\frac{1}{M}\sum_{m=1}^{M} PQ_{h,c,k,\phi(h)-m}}$
$PQ_{h,c,k,t}$	*Category purchase quantity*	(Seasonality-corrected[a]) quantity (expressed in volume units, e.g. kilograms/liters) purchased by household *h* of category *c* in chain *k* during month *t*.
EPL proliferation		
$EPL_{h,c,k}$	*EPL presence at hard-discounter entry*	Dummy indicator, equals 1 when any EPL SKUs are available for category *c* in chain *k* at the time of HD entry in household *h*'s local market, 0 otherwise
Controls: Demographics		
$HHsize_{h}$	*Household size*	Number of household members of household *h*
$Children_{h}$	*Number of children*	Number of child members (age<18) of household *h*
$Income_{h}$	*Household income*	Net monthly income (in thousands of euros) of household *h*
$DualInc_{h}$	*Dual-income household*	Dummy indicator, equals 1 if household *h* is a dual-income household, 0 otherwise
Age_{h}	*Age of household head*	Age (in years) of the head of household *h*
Controls: (Changes in) Marketing mix		
$\Delta Price_{h,c,k}$	*% change in category price*	$\left(\frac{1}{M}\sum_{m=1}^{M} Price_{c,k,\phi(h)+m} - \frac{1}{M}\sum_{m=1}^{M} Price_{c,k,\phi(h)-m}\right) / \left(\frac{1}{M}\sum_{m=1}^{M} Price_{c,k,\phi(h)-m}\right)$
$\Delta Assort_{h,c,k}$	*% change in assortment size*	$\left(\frac{1}{M}\sum_{m=1}^{M} Assort_{c,k,\phi(h)+m} - \frac{1}{M}\sum_{m=1}^{M} Assort_{c,k,\phi(h)-m}\right) / \left(\frac{1}{M}\sum_{m=1}^{M} Assort_{c,k,\phi(h)-m}\right)$
$\Delta SPL_{h,c,k}$	*% change in standard PL proliferation*	$\left(\frac{1}{M}\sum_{m=1}^{M} SPL_{c,k,\phi(h)+m} - \frac{1}{M}\sum_{m=1}^{M} SPL_{c,k,\phi(h)-m}\right) / \left(\frac{1}{M}\sum_{m=1}^{M} SPL_{c,k,\phi(h)-m}\right)$
$\Delta Promo_{h,c,k}$	*Change in promotional activity*[a]	$\frac{1}{M}\sum_{m=1}^{M} Promo_{c,k,\phi(h)+m} - \frac{1}{M}\sum_{m=1}^{M} Promo_{c,k,\phi(h)-m}$
$Price_{c,k,t}$	*Category price*	Average price per volume unit, across all non-EPL SKUs sold in category *c* by chain *k* in month *t*.
$Assort_{c,k,t}$	*Category assortment size*	Number of unique non-EPL SKUs sold in category *c* by chain *k* in month *t*.
$SPL_{c,k,t}$	*Category standard PL proliferation*	Number of unique standard PL SKUs sold in category *c* in chain *k* and month *t*, relative to category *c*'s assortment size.
$Promo_{c,k,t}$	*Category promotional activity*	Dummy indicator, equals 1 if any SKUs in category *c* are on featured promotion in chain *k* and month *t*, 0 otherwise.
Controls: (Changes in) Store distance		
$\Delta DistHD_{h}$	*Change in travel distance to hard-discounter*	$\frac{1}{M}\sum_{m=1}^{M} DistHD_{h,\phi(h)+m} - \frac{1}{M}\sum_{m=1}^{M} DistHD_{h,\phi(h)-m}$
$\Delta Dist_{h,k}$	*Change in travel distance to chain*	$\frac{1}{M}\sum_{m=1}^{M} Dist_{h,k,\phi(h)+m} - \frac{1}{M}\sum_{m=1}^{M} DistHD_{h,k,\phi(h)-m}$
$DistHD_{h,t}$	*Travel distance to hard-discounter*	Euclidean distance between household *h*'s home and the nearest outlet of a hard-discounter chain, measured in kilometers.
$Dist_{h,k,t}$	*Travel distance to chain*	Euclidean distance between household *h*'s home and the nearest outlet of chain *k*, measured in kilometers.

[a] We use absolute instead of percentage changes for promotional activity, due to the possibility of zero-values (i.e. no promotional activity) in the pre-entry period.

distance to the nearest HD outlet between the pre- and post-entry periods. This variable thus reflects the increase in accessibility of the HD format to household *h* as a result of local HD entry. Similarly, $\Delta Dist_{h,k}$ is the change in household *h*'s travel distance to the nearest outlet of traditional chain *k* pre- and post-entry. By including this variable, we control for changes in category purchase behavior that should not be attributed to the HD entry, but rather to contemporaneous changes in the traditional retailer's own outlet density.

Finally, the control variables $\Delta Price_{h,c,k}$, $\Delta Assort_{h,c,k}$, $\Delta SPL_{h,c,k}$ and $\Delta Promo_{h,c,k}$ reflect (percentage) changes in traditional retailers' average category price, assortment size, standard private label proliferation and promotional activity in the four months before and after the HD entry, respectively. These variables thus control for any concurrent sales effects of retailers' own marketing activities. Note that we do not take EPL SKUs into account when computing these price, assortment and private label controls. In this manner, we avoid that (part of) the EPL effect that we wish to capture in the parameter $\beta_{2,s}$ is incorporated in the marketing mix parameters instead.

To facilitate interpretation, we mean-center the household-demographics prior to estimation. Details on the measurement of the independent variables can be found in Table 3.2.

Table 3.3 provides category-level descriptives for some key variables. The table clearly reveals that, on average, consumers buy less from traditional supermarkets in the period after HD entry (negative sign for "ΔPurchase quantity" in the vast majority – i.e. 45 out of 48 – categories). Such losses occur for each of the traditional chains and, at least for some categories, appear to be quite severe. However, these figures do not yet provide a clean picture: some of the sales shifts possibly being due to other factors. Indeed, though Table 3.3 shows that the chains' marketing mix remains relatively stable around HD entry – which can

TABLE 3.3
Data Descriptives[a]

Product category	ΔPrice	ΔAssortment	ΔSPL proliferation	ΔPromotion	ΔPurchase quantity
Air freshener	**.015** (.047)	**.076** (.121)	**.000** (.000)	**-.034** (.172)	**-.499** (1.167)
Baking products	**.005** (.027)	**-.002** (.100)	**.027** (.219)	**-.082** (.218)	**-.279** (.841)
Bread	**-.096** (.088)	**-.136** (.209)	**.650** (1.326)	**-.015** (.283)	**-.515** (1.083)
Butter cakes	**.003** (.056)	**.098** (.215)	**.047** (.164)	**-.032** (.243)	**-.511** (.968)
Canned meat	**-.013** (.033)	**.008** (.063)	**-.003** (.063)	**-.199** (.230)	**-.296** (1.154)
Canned vegetables	**.005** (.037)	**.020** (.052)	**.044** (.078)	**-.108** (.312)	**.023** (1.271)
Cheese spread	**-.048** (.063)	**-.059** (.117)	**.073** (.124)	**-.062** (.265)	**-.429** (.924)
Coffee	**-.002** (.047)	**.084** (.060)	**-.028** (.081)	**.000** (.000)	**-.049** (1.303)
Coffee creamer	**-.015** (.083)	**.012** (.099)	**.003** (.062)	**-.025** (.101)	**-.495** (.580)
Cold cuts	**.003** (.015)	**.008** (.087)	**.166** (.366)	**-.026** (.249)	**.077** (1.248)
Cookies	**.000** (.032)	**.009** (.157)	**.298** (.631)	**-.063** (.241)	**-.183** (1.189)
Dry biscuits	**-.004** (.046)	**.018** (.062)	**.048** (.135)	**.086** (.313)	**-.301** (1.098)
Eggs	**-.002** (.063)	**.031** (.076)	**.128** (.224)	**-.001** (.327)	**-.187** (1.033)
Fabric softener	**.052** (.052)	**.118** (.098)	**-.105** (.126)	**-.081** (.287)	**-.418** (.977)
Fresh vegetables	**-.002** (.066)	**.040** (.108)	**.006** (.162)	**.095** (.428)	**.155** (1.301)
Fruit compote	**.044** (.122)	**.001** (.085)	**.001** (.189)	**-.027** (.347)	**-.106** (1.147)
Frying fat	**.033** (.052)	**.059** (.092)	**-.024** (.083)	**-.134** (.415)	**-.707** (.590)
Grated cheese	**.003** (.037)	**.055** (.239)	**.056** (.134)	**-.063** (.172)	**-.318** (1.030)
Gravy products	**-.038** (.053)	**.026** (.115)	**.000** (.000)	**.004** (.438)	**-.227** (1.657)
Hair gel	**-.000** (.150)	**.096** (.159)	**-.053** (.236)	**.033** (.176)	**-.402** (1.160)
Hard cheese	**-.002** (.018)	**.029** (.051)	**.005** (.391)	**.121** (.398)	**-.191** (1.133)
Jam	**.024** (.084)	**.036** (.131)	**.039** (.220)	**.029** (.294)	**-.403** (.776)
Ketchup	**-.013** (.066)	**.038** (.058)	**.138** (.378)	**.172** (.168)	**-.565** (.740)
Liquid detergent	**-.011** (.050)	**.130** (.106)	**-.078** (.097)	**.000** (.000)	**-.299** (1.274)
Margarine	**.083** (.063)	**.039** (.053)	**.006** (.126)	**-.034** (.270)	**-.248** (.999)
Microwave meals	**.031** (.029)	**.079** (.058)	**.014** (.052)	**.000** (.106)	**-.194** (1.316)
Milk	**-.020** (.039)	**-.023** (.047)	**.042** (.044)	**-.121** (.240)	**-.079** (1.150)
Muesli	**.007** (.037)	**.010** (.061)	**.043** (.153)	**.026** (.290)	**-.129** (1.535)
Mustard	**.010** (.085)	**.089** (.141)	**.000** (.000)	**.004** (.033)	**-.614** (.721)
Oils	**.039** (.076)	**.036** (.077)	**-.005** (.153)	**-.148** (.233)	**-.317** (1.297)
Pancake mix	**.073** (.109)	**.069** (.203)	**.177** (.418)	**.029** (.326)	**-.232** (1.776)
Pasta sauce	**-.006** (.043)	**.059** (.045)	**.120** (.325)	**.085** (.231)	**-.382** (.993)
Peanuts and nuts	**-.010** (.027)	**.035** (.096)	**-.028** (.066)	**-.060** (.260)	**-.286** (1.159)
Powder detergent	**.008** (.038)	**.048** (.094)	**-.034** (.154)	**.000** (.000)	**-.407** (.927)
Prepared meat	**.028** (.034)	**.068** (.080)	**.287** (.261)	**-.187** (.273)	**-.083** (1.330)
Rye bread	**-.006** (.040)	**-.012** (.106)	**.094** (.274)	**-.013** (.085)	**-.452** (.881)
Salad dressing	**.058** (.062)	**.048** (.130)	**.038** (.401)	**-.060** (.406)	**-.241** (1.371)
Salads	**.020** (.051)	**.070** (.139)	**.160** (.478)	**.041** (.489)	**-.335** (1.402)
Sandwich salads	**.032** (.047)	**.051** (.086)	**.200** (1.026)	**.024** (.148)	**-.148** (1.213)
Sausages	**-.034** (.062)	**-.214** (.315)	**.297** (.346)	**-.400** (.452)	**-.927** (1.260)
Shampoo	**.026** (.080)	**.030** (.117)	**.168** (.687)	**-.030** (.173)	**-.628** (.853)
Spaghetti	**.008** (.080)	**-.000** (.065)	**.023** (.096)	**.102** (.404)	**-.564** (.746)
Sprinkles	**.025** (.053)	**.065** (.077)	**.119** (.285)	**.044** (.228)	**-.172** (1.241)
Tea	**.018** (.035)	**.045** (.086)	**-.025** (.057)	**-.213** (.316)	**-.117** (1.327)
Toilet paper	**.013** (.040)	**.051** (.068)	**-.054** (.059)	**-.004** (.030)	**-.201** (1.239)
Vermicelli	**.037** (.081)	**-.059** (.088)	**.000** (.000)	**.049** (.177)	**-.693** (.512)
Vinegar	**.080** (.231)	**.074** (.100)	**-.018** (.097)	**-.063** (.236)	**-.696** (.694)
Waffles	**-.007** (.065)	**.022** (.101)	**-.060** (.229)	**.134** (.480)	**-.458** (1.045)

[a] Mean values (standard deviations) are in bold (in brackets), and are computed across households and chains.

be explained by the chains' centralized management – some shifts do occur.[21] Moreover, the question remains whether these losses can be mitigated by carrying an EPL in the category.

Based on the rough data, it appears that having an EPL helps to counter the HD threat: in the presence of EPLs, we observe smaller losses from HD entry for 62.5% of the categories – although on average, these reductions are limited in size (5.91%). At the same time, however, the standard deviation across categories is substantial, and it is unclear to what extent the effect is due to local market differences (i.e. differences in household profiles or distance to the new HD) rather than EPL presence as such. For a clean assessment of the EPL effect, we use the model presented in equation [3.1], which allows us to control for these confounds.

3.5 Results

Sample selection

We estimate our model on a dataset pertaining to 48 categories in which Super de Boer introduced its EPL. However, Super de Boer most likely did not choose these categories at random. Rather, they may be the categories in which the EPL was deemed most effective, or categories in which the impact of HD entry was expected to be most severe. This creates a sample selection problem, which we need to correct for to avoid bias in the parameter estimates (Hamilton and Nickerson 2003). We do so by applying Heckman's traditional two-step procedure (Heckman, 1979). This procedure requires us to first specify a "selection equation" that links the retailer's decision whether or not to introduce an EPL in a category, to a set of relevant category characteristics. We include three sets of such characteristics. The first group of characteristics (category penetration, purchase frequency and sales growth)

[21] We note that, since Dutch retailers are managed centrally and, accordingly, our marketing mix measures are calculated at the chain (not the store) level, these shifts cannot follow from the specific HD opening itself (which is location-specific), but just happen to co-occur.

reflects the category's (monetary) importance to a retailer (Ter Braak 2012). As such, they may help the retailer in judging whether the category is worth the investment of developing and carrying an EPL. The second group (promotion frequency, standard private label proliferation and standard private label price advantage (over national brands)) indicates to what extent the retailer's current category offer already caters to price-sensitive consumers. Retailers may use this information to evaluate whether an EPL will be of added value for a category. Finally, as retailers have shown to be quite eager in matching competitors' price-related marketing activities (e.g. Van Heerde et al. 2008), we include the EPL proliferation of competing retailers in the selection equation as well. Table 3.4, panel A provides more details on the included characteristics, along with their operationalization. The (probit) selection model, which is to be estimated on the total set of categories, takes the following form (where $EPLcarried_c$ is a binary indicator that equals 1 if Super de Boer carried an EPL in category *c* at any time during our 2005-2006 observation period and 0 otherwise; and $EPLcarried_c^*$ is a latent variable capturing the attractiveness of carrying an EPL in category *c*):

$$\begin{aligned} EPLcarried_c^* = {} & \varphi_0 + \varphi_1 * Penetration_c + \varphi_2 * Frequency_c + \varphi_3 * Growth_c \\ & + \varphi_4 * Promo\_freq_c + \varphi_5 * SPL\_proliferation_c + \varphi_6 * SPL\_pricediff_c \\ & + \varphi_7 * EPLcomp_c + u_c \\ EPLcarried_c = {} & \begin{cases} 1 \; if \;\; EPLcarried_c^* > 0 \\ 0 \; if \;\; EPLcarried_c^* \leq 0 \end{cases} \end{aligned} \tag{3.3}$$

The estimated selection model does quite well in distinguishing the sampled categories from the remaining categories: 86.5% of the categories in which Super de Boer carries an EPL, are correctly predicted as such by the model (for the cutoff point, we use the percentage of categories in which an EPL is carried). As shown in Table 3.5, Super de Boer primarily offers an EPL in categories that are frequently purchased, and in which its competitors have an EPL as well. Following the procedure of Heckman (1979), we use the

TABLE 3.4
Variable Operationalizations (Category Factors)

Notation	Variable name	Operationalization
PANEL A: SELECTION MODEL		
$Penetration_c$	*Penetration*	(Year) average share of the retailer's[a] customers that bought category *c* at least once.
$Frequency_c$	*Purchase frequency*	(Year) average number of weeks in which a category purchase was made by the retailer's customers who buy in category *c*.
$Growth_c$	*Sales growth*	(Year) average percentual growth of the retailer's volume sales in category *c*.
$Promo\_freq_c$	*Promotion frequency*	(Year) average share of the retailer's national brand volume sales in category *c* that were made on price promotion.
$SPL\_proliferation_c$	*Standard private label proliferation*	(Year) average assortment share of the retailer's standard private label in category *c*.
$SPL\_pricediff_c$	*Standard private label/national brand price difference*	(Year) average ratio of category *c*'s leading national brand's (SKU-weighted) price at the retailer, to the retailer's standard private label's (SKU-weighted) price.
$EPL\_competition_c$	*Competitors' EPL proliferation*	Dummy indicator, equals 1 if any of the retailer's competitors[b] already[c] carried an EPL in category *c*, 0 otherwise
PANEL B: OTHER FACTORS		
$Hedonic_c$	*Hedonic (vs. functional) product*	Averaged expert rating [d] (on 5-point Likert scale) of the degree to which products in category *c* are primarily evaluated in terms of hedonic product characteristics (instead of functional product features) (Cronbach's α: .817).
$Visibility_c$	*Visibility of consumption*	Averaged expert rating (on 5-point Likert scale) of the degree to which products in category *c* are publicly consumed (Cronbach's α: .708).
$Differentiation_c$	*Product differentiation*	(Year) average number of unique SKUs carried by the retailer in category *c*
$Qual\_var_c$	*Quality variability*	Averaged expert rating (on 5-point Likert scale) of the degree to which products in category *c* vary in quality (Cronbach's α: .761).
HD_SKUs_c	*Number of SKUs at hard-discounter*	(Year) average number of unique SKUs carried by hard-discounters (averaged across Aldi and Lidl), in category *c*.
EPL_order_c	*EPL introduction order*	Month (ranging from January 2005 (1) to December 2006 (24)) in which the retailer introduced its EPL in category *c*.
$HD\_EPL\_pricediff_c$	*Hard-discounter/EPL price difference*	(Year) average ratio of category *c*'s (SKU-weighted) price at hard-discounters (averaged across Aldi and Lidl), to the retailer's economy private label's (SKU-weighted) price.

[a] In the context of this study, we operationalize these characteristics for Super de Boer.
[b] Albert Heijn is the only relevant competitor here, being the only one that carried an EPL before Super de Boer.
[c] As Super de Boer mainly rolled out its EPL in 2005 and 2006, we measure the EPL proliferation of competitors at the end of 2004.
[d] The category characteristics "hedonic (vs. functional) product", "visibility of consumption" and "quality variability" are assessed through a survey, filled in by three experts (see Appendix 4 for the specific items that were used). With regard to inter-rater reliability, an average Spearman correlation coefficient of .6 was obtained across scales and expert pairs.

selection model parameters to compute the inverse Mills ratio for each category in our final sample, and include it as an additional explanatory variable in our main model (see equation [3.1]).While this approach will alleviate the bias in the main model's parameter estimates, it also introduces heteroscedasticity into the error term. We therefore apply weighted least squares, to make the parameters' standard errors unbiased as well (Smits 1999).

TABLE 3.5
Parameter Estimates (Selection Equation)

Parameter		Estimate[a]
Intercept	(φ_0)	**-2.117** (-3.275)
Penetration	(φ_1)	.021 (.019)
Purchase frequency	(φ_2)	**.191** (2.212)
Sales growth	(φ_3)	-.225 (-.407)
Promotion frequency	(φ_4)	.939 (.231)
Standard private label share	(φ_5)	.607 (.148)
Standard private label-national brand price difference	(φ_6)	-.064 (-.429)
Competitors' EPL proliferation	(φ_7)	**1.214** (5.532)

[a] Estimates significant at the 5% level (two-sided) are portrayed in bold. Values in brackets represent t-values for the coefficients.

Main model results

Table 3.6 reports fit statistics for the one- to four-class solutions. We retain three classes (i.e. groups of categories), as this solution yields the best fit in terms of BIC and CAIC. Table 3.7 reports the parameter estimates for the three groups (which include 46%, 35% and 19% of the categories, respectively), while Table 3.8 displays which categories each group comprises.

TABLE 3.6
Model Fit

		Fit			
# classes	**# parameters**	***AIC***	***AIC3***	***BIC***	***CAIC***
1	18	18496	18514	18526	18544
2	25	18301	18326	18344	18369
3	32	18248	18280	18303	18335
4	39	18238	18277	18305	18344

Before turning to the key parameters, we note that the coefficient of the inverse Mills ratio is significant. Its negative sign implies that the error terms of the selection equation and the main model are negatively correlated: Super de Boer thus primarily introduces an EPL in

TABLE 3.7
Parameter Estimates[a]

	Parameter		Class 1 46%	Class 2 35%	Class 3 19%
Class-specific parameters	***(Chain) intercepts***				
	Intercept	(β_0)	.039	**-.268**	**-.550**
			(.777)	(-4.735)	(7.348)
	Albert Heijn (reference)				
	C1000	($\beta_{1,1}$)	-.034	.026	**.239**
			(-.677)	(.439)	(2.830)
	Plus	($\beta_{1,2}$)	-.113	-.102	-.020
			(-1.368)	(-1.085)	(-.150)
	Super de Boer	($\beta_{1,3}$)	**-.214**	-.024	-.066
			(-2.055)	(-.206)	(-.443)
	EPL proliferation				
	EPL presence	(β_2)	.044	.128	**.583**
			(.355)	(.926)	(3.120)
Class-independent parameters	***Household demographics***				
	Household size	(δ_1)	.016	.016	.016
			(.880)	(.880)	(.880)
	Number of children	(δ_2)	-.041	-.041	-.041
			(-1.582)	(-1.582)	(-1.582)
	Income	(δ_3)	*.036*	*.036*	*.036*
			(1.862)	(1.862)	(1.862)
	Dual-income	(δ_4)	-.002	-.002	-.002
			(-.030)	(-.030)	(-.030)
	Age	(δ_5)	.001	.001	.001
			(1.163)	(1.163)	(1.163)
	Store distance				
	Change in distance to HD	(δ_6)	.001	.001	.001
			(.057)	(.057)	(.057)
	Change in distance to chain	(δ_7)	**-.427**	**-.427**	**-.427**
			(-3.942)	(-3.942)	(-3.942)
	Marketing mix				
	(%) change in price	(λ_1)	**-.681**	**-.681**	**-.681**
			(-2.989)	(-2.989)	(-2.989)
	(%) change in assortment size	(λ_2)	**.850**	**.850**	**.850**
			(6.663)	(6.663)	(6.663)
	(%) change in SPL proliferation	(λ_3)	.019	.019	.019
			(.449)	(.449)	(.449)
	Change in promotional activity	(λ_4)	**.244**	**.244**	**.244**
			(4.941)	(4.941)	(4.941)
	Correction for sample selection				
	Inverse Mills ratio	(ψ)	**-.144**	**-.144**	**-.144**
			(-3.081)	(-3.081)	(-3.081)

[a] Estimates significant at the 5% (10%) level (two-sided) are portrayed in bold (italics). Values in brackets represent z-values for the coefficients.

categories for which the sales loss after HD entry is high. Also, most of the control variables have a significant effect. As expected, price reductions, assortment extensions and increases in promotional activity make the retailer's customers buy more from the category.

TABLE 3.8
Category Allocation to Latent Classes (Category Groups)

Class 1	Class 2	Class 3
Canned meat[a]	Air freshener	Coffee creamer
Canned vegetables	Baking products	Frying fat
Coffee	Bread	Jam
Cold cuts	Butter cakes	Ketchup
Cookies	Cheese spread	Mustard
Fresh vegetables	Dry biscuits	Shampoo
Fruit compote	Eggs	Spaghetti
Gravy products	Fabric softener	Vermicelli
Hard cheese	Grated cheese	Vinegar
Liquid detergent	Hair gel	
Microwave meals	Margarine	
Milk	Pasta sauce	
Muesli	Peanuts and nuts	
Oils	Powder detergent	
Pancake mix	Rye bread	
Prepared meat	Sausages	
Salad dressing	Waffles	
Salads		
Sandwich salads		
Sprinkles		
Tea		
Toilet paper		

[a] Categories are allocated to classes based on their posterior class-membership probabilities.

Moreover, we find that when the distance between a household and a traditional retailer becomes smaller/larger (e.g. because the retailer opens a new outlet or closes a current one down), more/less is bought from the retailer. Hence, separating out these effects turns out to be important to get a clean estimate of the impact of HD entry and EPL presence.

Our primary interest, however, lies in the parameters that capture the category sales impact of HD entry on traditional retailers, and whether this impact is moderated by the presence versus absence of an EPL.

Sales impact of hard-discounter entry

From the estimated (chain) intercepts across latent classes, it becomes apparent that traditional retailers can suffer substantial losses from HD entry,[22] but that the effect differs widely across categories. For Albert Heijn, the loss from HD entry in categories of group *s* is reflected in the estimate for $\beta_{0,s.}$ For C1000, Plus and Super de Boer, we test this HD entry effect by assessing the significance of the associated combination of intercepts (e.g. for C1000, we test the significance of $\beta_{0,s}+ \beta_{1,1,s}$). We find that in group 1, the HD entry effect is not significantly different from zero for any of the four traditional chains. For this group of categories, local HD entry does not appear to entail a systematic sales drop – which may indicate that the purchase of these categories is strongly tied to the traditional supermarket format (Inman et al. 2004). In group 2, however, traditional retailers do seem to be (adversely) affected by local HD entry – the entry effect being negative and significant for all four chains (which is in line with the descriptives in Table 3.3). These effects are quite considerable: after local HD entry, customers' category purchase quantity is reduced by about 30% on average. Finally, even more pronounced entry losses are observed in the third group of categories, and these losses are again significant for all chains (characteristics that can explain these differences are discussed in the section on "category group profiles").

Given that the household variables are mean-centered, the previously discussed loss figures apply to the average household. While these losses are likely to differ across households, our results indicate that demographics have low explanatory power in this regard. This is not uncommon: other studies on customer defection to discounters (e.g. Singh et al.

[22] Unlike prior studies (e.g. Cleeren et al. 2010), we do not explicitly make a distinction between HD outlets that are the 'first of their kind' to enter a local market, and HD outlets that open up subsequently. This is mainly because the number of 'first-mover' entries in our sample is fairly small: during the pre-entry period, only 8% of households did not yet have a HD located within a 5 km radius. Moreover, we already incorporate a 'change in travel distance to the HD'-variable – which is likely to be much larger in magnitude for first-mover entries (since the household did not have an HD outlet nearby prior to entry). However, this variable is not significant in our final model, which makes it unlikely that substantial differences exist in the category sales impact of first-mover and subsequent HD entries.

2006) come to a similar conclusion. We do obtain a marginally significant effect for income, and find that less affluent households shift a larger share of their purchases away from the traditional supermarket after HD entry (which makes sense, given the tighter budget of these households).

Effectiveness of EPLs

The question central to our paper – whether carrying an EPL helps traditional retailers defend against local HD entry – can be assessed from the parameter β_2. This parameter is not significant for category groups 1 and 2, implying that carrying an EPL in these categories will neither mitigate nor amplify the sales loss for a traditional retailer after HD entry. For group 3 however, the EPL presence parameter is significant, and has a positive sign. For categories in this group, carrying an EPL at the time of HD entry thus lowers the sales loss for the traditional retailer. Specifically, we find that for group 3, the parameter combination $\beta_0+\beta_{1,3}+\beta_2$ (which is the total HD entry effect for Super de Boer when it carries an EPL) does not significantly differ from zero (p-value .82). This implies that, for the average household, offering an EPL in the categories of group 3 successfully prevents Super de Boer from losing household purchases in these categories after HD entry.

Category group profiles

Table 3.9 displays the position of the three category groups along two dimensions: the nature of the HD entry effect and the effectiveness of EPLs. Two things catch the eye. First, for a considerable number of categories in which an EPL is introduced (group 1, 46% of categories), local HD entry does not seem to systematically affect traditional retailers' sales – regardless of whether an EPL is present. Second, while EPLs prove to be an effective defense tool in categories where traditional retailers suffer the most severe losses after HD entry, they do not seem to work positively in categories where retailers are less vulnerable.

TABLE 3.9
Category Group Characterization

		Change in category sales after hard-discounter entry	
		No changes	***Sales loss***
Effect of EPL presence	***No effect***	Class 1 (22 categories) *(e.g. canned vegetables, cold cuts, milk)*	Class 2 (17 categories) *(e.g. dry biscuits, eggs, peanuts and nuts)*
	Reduction of sales losses		Class 3 (9 categories) *(e.g. jam, ketchup, spaghetti)*

To get a feel for what drives these differences, we explore whether the class membership of the sample categories can be explained from category factors. Such factors may be "intrinsic" to the category, as well as more market-related. Based on the available data, and insights from previous literature on private label performance and store format choice, we consider as intrinsic characteristics the category's purchase frequency (Dawes and Nenycz-Thiel 2012; Dhar et al. 2001; Sethuraman 2003), its hedonic versus functional nature (Batra and Sinha 2000; Sethuraman 2003; Sethuraman and Cole 1999), the visibility of consumption in this category (Semeijn, Van Riel and Ambrosini 2004), the degree to which products in the category are differentiated (Inman et al. 2004) and the perceived variability in product quality (Batra and Sinha 2000; Hoch and Banerji 1993). As for the market-related characteristics, we include the traditional retailer's standard private label proliferation in the category (Dhar and Hoch 1997) and the order in which the EPL is introduced in the category by the retailer (Sayman and Raju 2004). Moreover, we include two factors affecting the comparative advantage of the HD's offer: the number of SKUs present in the HD's category assortment, and the price differential with the EPL. For information on the operationalization of these factors, see Table 3.4, panel B.

For each of the three category groups, we conduct ANOVAs to compare members and non-members of the group on these factors. Table 3.10 depicts the results, along with

TABLE 3.10
Category Factors across Classes and ANOVAs

Category factors	Class 1	Class 2	Class 3
Purchase frequency	**4.832**[a]	3.554	**2.184**
	(2.476)	(1.140)	(.337)
Hedonic (vs. utilitarian)	2.970	2.902	2.481
	(.809)	(.911)	(.899)
Visibility of consumption	2.227	2.137	1.889
	(.737)	(.817)	(.745)
Product differentiation	**131.345**	67.882	**31.267**
	(115.903)	(43.866)	(29.803)
Quality variability	**3.197**	2.882	<u>2.593</u>
	(.640)	(.707)	(.846)
Standard private label proliferation	.309	.292	.194
	(.180)	(.208)	(.197)
EPL introduction order	**12.364**	13.176	**14.444**
	(1.989)	(1.590)	(1.014)
Number of SKUs at HD	**35.909**	16.535	<u>7.028</u>
	(45.095)	(8.996)	(5.081)
Hard-discounter/EPL price difference	2.031	1.562	1.809
	(1.709)	(.910)	(1.443)

[a] Reported values are means and standard deviations (in brackets) for the category characteristics per class. Values in bold (underlined) are class means that significantly differ on a 5% (10%) level from the mean over the other two classes.

descriptives of the factors for each group. Our primary interest lies in the characteristics of groups 2 and 3, comprising the categories in which traditional retailers are vulnerable to HDs. Looking at the descriptives, group 2 – which holds categories for which EPLs do not help in mitigating the losses to HDs (such as dry biscuits, eggs, peanuts and nuts) – seems somewhat "average" on almost every characteristic. As such, a remarkable result is that this group does not significantly differ from the other two on any of the included characteristics. For this reason, the focus in the rest of the discussion below is on category group 3 instead, which holds the categories in which traditional retailers are (most) vulnerable to HDs, but where EPLs can help them effectively defend as well.

The ANOVA results indicate that categories in class 3 have a significantly lower purchase frequency compared to the remaining categories.[23] Moreover, categories in group 3

[23] Due to the exploratory nature of this analysis, and the small sample size for the ANOVAs (48 categories), we test significance at the 10% level. Also, because of this limited number of data points, we use separate ANOVAs for each variable.

seem to be rather homogeneous: they are relatively undifferentiated (few unique SKUs) and have the lowest perceived variability in quality. Though they are the least hedonic in nature, and show the lowest levels of consumption visibility, these effects are not significant. While EPL effectiveness appears to be related to the HD's assortment size – group 3 comprising categories for which the HD chain offers a smaller assortment – the magnitude of the price gap with the HD does not seem to matter. Interestingly, we find that EPL introduction order is significantly and positively related to class 3-membership, suggesting that EPLs become more effective as the rollout proceeds. The proliferation of the standard private label in the retailer's assortment, finally, is not linked to group membership.

Robustness checks

To check the robustness of our findings, we test several alternative specifications. First, we estimate a model in which the four-month post-entry period does not start in the month immediately following the HD entry, but one month thereafter. Openings of HD outlets may go together with special (promotional) activities aimed to attract traffic to the new store, and omitting the month immediately after HD entry allows us to assess whether our original findings are influenced by such activities. We find the pattern of results to be largely unaffected. Like before, we obtain one group of categories in which EPLs (significantly) lower HD-entry losses and, again, this is the group where the negative impact of HD entry on traditional chains is most severe.[24] Moreover, focusing on the differences in category characteristics between groups, we find the direction of effects to be the same as in Table 3.10. The differences remain significant for purchase frequency, product differentiation, EPL introduction order and the number of SKUs carried by HDs. In addition, the differences on hedonic (versus utilitarian) product and standard private label proliferation are now

[24] We do note that the group where the EPL effect is significant is now larger, and comprises nine extra categories.

significant as well (under a 10% and 5% level, respectively). We conclude that our results are fairly robust to the alternative operationalization of our post-entry period.

Second, we estimate three more variants of the model, each of which incorporates an additional control variable that was not included in the base model. We will discuss how each of these variables can help overcome a limitation of the base model, and present the results thereafter.

Interpurchase time. Although our approach of using a "fixed" four-month pre- and post-entry period for all categories has its advantages (i.e. it ensures comparability by covering the same shopping trips), it does not take differences in category purchase frequency into account. To control for these differences, we therefore include category interpurchase time (in weeks, averaged across households) as a first additional predictor.

Timing of HD entry. Our post-entry period comprises the four months following the month in which the HD entered. As such, for some HD entries, we measure the entry's impact some weeks after the outlet opened up (if the HD entered at the beginning of the month), while for others the impact is measured immediately after the outlet's opening (if the HD entered at the end of the month). To check whether these differences in timing affect the measured impact of HD entry, we include timing-of-entry (through week dummies) as a second additional predictor.

Local competition. While our base model recognizes that the impact of HD entry may depend on the entrant's own characteristics (e.g. through the travel distance variable, which indicates to what extent the entrant has made the HD format more accessible), it does not so much account for the competitive context in which the HD enters. However, the number of active competitors may actually influence households' response to the new HD – for example because it determines whether households were already able to "shop around" (and thereby save money) prior to the HD's entry. To check whether the impact of HD entry indeed depends on the competitive environment, we include the number of competing chains (within a 5 km radius from the household, at the time of HD entry) as a third additional predictor.

Though some of these additional variables prove significant (the impact of HD entry is significantly more negative in categories with a larger interpurchase time: p-value <.01, and for entries in the fourth week of the month: p-value <.01), the main pattern of results (direction, significance and relative magnitude of parameter estimates, and latent class membership) remains (virtually) the same (details can be obtained from the authors upon request). This lends further confidence to the robustness of our findings.

3.6 Discussion

The astounding rise of hard-discounters has triggered a quest for proper defense mechanisms among traditional retailers. Though economy private labels have been advanced by academics and practitioners as a potentially effective defense tool, empirical support for this contention has been limited at best. One explanation for this lack of evidence is the difficulty of isolating such "defensive" power of EPLs from other market changes. In this paper, we adopt a difference-in-difference methodology to a unique (scanner panel) data set for the Dutch grocery market – covering multiple openings of HD stores, as well as EPL introductions in multiple product categories. This approach allows us to provide some – to the best of our knowledge, first – empirical indications on the following issues. When a HD enters the trading zone of a traditional supermarket chain, what share of customers' category purchases is lost if the chain does not carry an EPL in that category? Does carrying an EPL mitigate these category sales losses? And: what explains the differences between categories in vulnerability to HD entry and, especially, the power of EPLs to counter the HD threat?

Vulnerability to hard-discounter entry in the absence of an EPL

As expected, local entry of a HD store in general makes traditional chain customers buy less from this chain. Using the parameters from our model, and aggregating the predicted sales volume losses from HD entry across the households and categories in our sample, we observe a sales loss that is quite substantial: 27.6%.[25] A striking observation is that this overall picture conceals dramatic category differences. Specifically, some categories, such as frying fat and jam, exhibit major purchase shifts away from traditional chains. In other categories, however, sales losses are less pronounced (i.e. roughly half as large, e.g. for eggs and sausages) or even remain virtually absent (e.g. for coffee and fresh vegetables). Hence, the "HD threat" unfolds itself as highly category-specific.

Defensive power of EPL

Likewise, the impact of having an EPL differs considerably between categories. In none of the product categories, the presence of an EPL amplifies the sales losses upon HD entry. Hence, it seems that for categories in which an EPL is carried, the EPL does not make consumers more susceptible to the HD format. In contrast, there is a small subset of categories where the presence of the low-tier EPL mitigates the sales losses from HD entry. This suggests that having access to a cheap alternative within the traditional chain, reduces the incentive for consumers to buy low-priced products at the new HD entrant. Interestingly, while EPLs prove to be a particularly effective defense tool in categories where traditional retailers incur major losses after HD entry, they do not improve post-entry sales in categories where retailers are less vulnerable. Taken together, this implies that if traditional retailers seek to shield themselves from HD entry with an EPL, but want to avoid "spoiling their arms", category selection becomes key.

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[25] Note again that for Albert Heijn, the observed shifts are incurred in the presence of the Euroshopper EPL. We therefore exclude Albert Heijn from the calculations in computing the aggregate sales loss.

In which categories are EPLs most promising?

To assist retailers in the identification of categories in which EPLs will have the highest "defensive ability", we offer some tentative links with category characteristics. EPLs seem most effective at reducing losses from HDs in categories with lower purchase frequency. This result is somewhat surprising, given that some prior studies find PL products to be more successful in frequently bought categories (e.g. DelVecchio 2001; Sethuraman and Cole 1999). An explanation may be that while it is easier for consumers to buy low-frequency goods at a HD (as it involves fewer additional store visits), the lower importance of these goods in their grocery budgets (Narasimhan and Wilcox 1998) may make consumers less intrinsically motivated to do so. As a result, having access to a low-priced EPL in these infrequently purchased categories may suffice to prevent consumers from buying them at a HD. This is in line with Dawes and Nenycz-Thiel (2012), who suggest that in categories with low purchase frequency, private label products may be more successful in tying consumers to the store.

We do not find the categories in which EPLs perform well vis-à-vis HDs, to be (significantly) less hedonic in nature. Similarly, categories where EPLs are effective defense tools are not necessarily the ones that are more privately consumed (and thus involve less social risk). The latter finding is in line with the premise that purchasing items at HDs (Steenkamp and Kumar 2009) and purchasing low-priced grocery items in general has become more socially acceptable, making this category characteristic irrelevant.

Instead, our results clearly show that EPLs are primarily effective in (relatively) undifferentiated categories, and do not work well in categories that involve a large number of brands and/or product varieties. For the latter type of categories, retailers may find it difficult to develop a focused store-brand strategy that is still able to appeal to the majority of category buyers (Dhar and Hoch 1997). While this holds for private label products in general, it may especially confine the retailer's ability to launch a successful EPL alternative, as EPL lines generally comprise very few items per category.

Moreover, variability in product quality is found to play a role – EPLs doing especially well in categories where this variability remains low. This is an intuitive result: due to their cheap production process, EPLs compare unfavorably to other products in the category when it comes to quality. However, the lower the category's variability in product quality, the smaller this gap will be – thus increasing the EPL's relative appeal. In contrast, both HDs and EPLs have a negligible impact in categories where perceived quality differences (and quality uncertainty) are high. In such categories, consumers are expected to rely more on renowned (national) brands (e.g. Batra and Sinha 2000; Erdem and Swait 1998). Naturally, this negatively affects the competitive position of both HD products and EPLs.

Turning to the market-related factors, we find that EPLs are better at keeping HDs at bay in categories where these HDs carry few SKUs. In such categories, EPLs – with their narrow depth – constitute a more viable alternative against the HD offer. The magnitude of the price gap, however, does not seem to matter; an observation also made by Nielsen (2007). In this respect, it is important to note that in each of the three category groups, the EPL price is – on average – below that of the HD chain.[26] Hence, it seems that in categories where the EPL does not have a large "assortment depth" disadvantage, being cheaper than the HD suffices to counter the sales loss.

The proliferation of the standard private label (SPL) in the retailer's assortment is not linked to HD losses or EPL power. This may be the result of a clearly differentiated multi-tier PL strategy (Geyskens et al. 2010), where higher-priced, high-quality SPLs are aimed to reduce the power of national brands, while EPLs primarily serve to fend off low-end price

[26] When we consider the categories one by one, we find that Super de Boer's EPL is priced below HD products for 37 out of 48 categories.

competition by HD alternatives. When both PL tiers target different competitors (national brands within the same store, versus PL products in a different store (i.c. the HD) (Dawes and Nenycz-Thiel 2012), the introduction and assortments of these tiers need not be fully aligned and can partly depend on other factors and considerations. This explanation is in line with the results of the selection model (Table 3.5), which demonstrates that the proliferation of SPL SKUs in the assortment has no substantial impact on the decision to introduce an EPL in the category.

Finally, it seems that EPL introduction in a category becomes more effective as the rollout proceeds. This may be the result of increased awareness of, or confidence in, the retailer's EPL tier. Also, consumers may only refrain from patronizing the HD if cheap alternatives are available in a wide enough range of categories. For traditional retailers, this implies that a sufficiently broad rollout is needed for the EPL program to become effective in keeping HDs at bay.

3.7 Limitations and Future Research

As our study is clearly not without limitations, many issues are still open for future work. We discuss these research opportunities below.

First, our endeavor to separate out the HD entry losses and EPL moderating effects as cleanly as possible through a difference-in-difference approach, comes at a price. We consider only households in markets where a new HD outlet opened up, and active in the panel during the four months preceding and following this entry. More importantly, our analysis was necessarily confined to the subset of categories wherein an EPL was introduced in the course of our observation period. Though the considered categories cover a broad range of items, it would be interesting to replicate our findings for other categories as well.

Second, our estimates of the EPL effect pertain only to the chain that rolled out its EPL during our observation period (i.c. Super de Boer). However, the effectiveness of an EPL may very well depend on how the EPL fits the store that carries it – something our data, unfortunately, did not allow us to test. As such, we leave it as a topic for further study. Similarly, the vulnerability of traditional chains to HDs (across different categories) was only assessed for a limited number of retailers (i.c. Albert Heijn, C1000, Plus and Super de Boer). It should, however, be noted that these were the chains most relevant to our study, as they were all active on a national level, and have a private label program that is sufficiently sophisticated (i.e. multi-tiered) to allow for the listing of an EPL as well.

Third, we reverted to typical characteristics (e.g. quality, packaging) of EPLs to develop arguments on why they can (not) be effective vis-à-vis HDs. However, the positioning of EPLs across retailers (and even categories) is not necessarily a given, and some variations may exist. For instance, an emerging practice is for retailers (e.g. Tesco) to develop a budget private label that does not necessarily offer the lowest price possible, but does match HDs in terms of product quality – and generally has more attractive packaging as well (Financial Times 2008). While such "discount brands" are thus less of a price-based response than EPLs, their quality gap with products sold at HDs is much smaller (both in an objective and perceived sense, due to the improved packaging; Steenkamp, Van Heerde and Geyskens 2010). This may make these brands an effective way to combat HDs in their own right. Given our finding that EPLs, though powerful in some categories, do not act as an effective defensive mechanism in many others, it is interesting to explore the defensive ability of discount brands (or other variations of EPLs) as well.

Fourth, our time span to assess the sales impact of local HD entry is relatively short (that is, an eight-month window around the HD's date-of-entry). While this reduces potential confounding effects, it also implies that we capture the impact of HD entry, and the moderating role of EPLs therein, on a short-term basis only. As such, the permanent effects of HD entry may actually have been understated (in case households need some time to notice or "warm up" to the new entrant) or overstated (if many early visits to the HD were for trial purposes only). To obtain a more complete picture on the impact of the HD threat and the degree to which EPLs can help mitigate it, future studies in this area could adopt a longer-term perspective.

Fifth, because we use local HD entry as our research setting, we assess the defensive ability of EPLs from a preemptive standpoint. In other words, we study whether carrying an EPL makes a retailer less vulnerable to any subsequent HD entries. While many retailers indeed stock EPLs in anticipation of HD entry (Just-Food 2006), others use them more as a counter-mechanism – and only introduce them after the initial impact of HD entry is felt (Coriolis Research 2002). Even though we find that EPLs can prevent traditional retailers' customers from switching to a HD, we cannot necessarily conclude the reverse – that is, whether the introduction of an EPL can help traditional retailers regain customers that were lost to the HD. To obtain a more complete picture of the effectiveness of EPLs in the battle against HDs, future research should therefore explore this issue as well.

Finally, while our results indicate that EPLs shield the store against HDs in only a limited subset of categories, this does not imply that EPL introductions in other categories are fruitless. Though EPLs are often introduced to counter the HD threat, they may be carried for other purposes as well, such as to foster further growth of the retailer's private label share, or as a means to build or reinforce a distinctive store image (Symphony IRI 2011). A thorough overview of categories in which EPLs should or should not be introduced may take these other purposes into account as well: issues that we leave for further research.

Chapter 4 Save or (Over-)Spend? How Shopping Pattern Choice Affects Consumer Grocery Spending

4.1 Introduction

The diversity of today's grocery retailing environment allows consumers to engage in a multitude of different shopping strategies or patterns. Rather than repeatedly visiting a single (most preferred) store to buy their groceries, consumers can decide to patronize multiple stores, on separate or chained (combined) store trips, and can choose between several differently positioned store formats. Previous studies indicate that shopping patterns involving a single store have become the exception rather than the rule (Fox and Hoch 2005; Gijsbrechts et al. 2008; Stassen et al. 1999). Among US shoppers, Fox (2005) observes that only 15% are "store/format loyal", i.e. allocate more than 70% of their grocery trips to their favorite supermarket store, the remaining households (85%) spreading their purchases across multiple chains and formats. Similarly, following a recent survey, 87% of Dutch shoppers buy their groceries at more than one supermarket banner (on separate or combined trips), the average number of chains visited by a household being equal to 2.8 (EFMI and CBL 2010).

While such more "involved" shopping patterns can also result from situational factors (i.e. idiosyncratic shopping locations or needs, Krider and Weinberg 2000; Fox 2005), they mainly stem from consumers shopping "strategically" (Fox 2005). By organizing their grocery shopping in a certain way, consumers hope to systematically reap higher shopping utility, and be able to buy their products at the best possible value (Gijsbrechts et al. 2008). Savings play an important part in this matter. Indeed, several marketing scholars identify "shopping cost minimization" as the major reason for consumers to engage in multiple-store shopping, to prefer combined over separate shopping trips and/or to select a specific (combination) of store format(s) (e.g. Fox and Hoch 2005; Galata, Bucklin and Hanssens 1999; Mägi and Julander 2005). Consumers may, for example, visit an additional store to benefit from an increased number of price promotions (Fox and Hoch 2005), or shop at a “hard-discounter” to save money in categories where brand equity is less important to them (Costa et al. 2006). Especially in times of low consumer confidence, such practices gain importance: a 2010 EFMI and CBL survey indicating that in order to cut their grocery spending, 40% of shoppers increased the number of chains that they visit, and 12% switched to another store (format) (EFMI and CBL 2010).

However, even though alternative shopping patterns may give access to lower prices and provide a means to economize on grocery expenditures, it is not obvious that such savings will actually be realized by consumers. To realize intended outcomes, consumers need more than just having access to the right opportunities – they also require the ability to take advantage of these opportunities, as well as the motivation to undertake the necessary actions (e.g. Batra and Ray 1986; MacInnis and Jaworsky 1989). Choice of a shopping pattern impacts on all three components. It not only affects the potential (opportunity) for savings, but also consumers’ ability to spot these savings, and their motivation to behave consistently with the savings goal. For example, visiting more than one store implies that consumers will be confronted with a variety of different assortments and prices. This may severely complicate the price comparison process (and thus decrease the consumer’s ability to spot attractive prices), and lead to increased exposure to in-store incentives (which stimulate unplanned purchases, and thus make consumers less motivated to stick to their savings objective). Also, depending on whether consumers opt for “traditional” (Hi-Lo) or (hard-)discounter (EDLP) stores, and whether they visit different stores on separate or combined trips, they may encounter fewer opportunities to take advantage of attractive price deals, be less able to accurately track their expenditures, and/or lose their motivation to save as a result of in-store stimuli (e.g. Gauri, Sudhir and Talukdar 2008; Heilman, Nakamoto and Rao 2002; Van Ittersum, Pennings and Wansink 2010). It follows that while some shopping patterns allow consumers to save money, consumers may not capitalize on this opportunity because they are unable to correctly perceive it or because they become distracted from the savings goal.

The question thus remains whether, and to what extent, shifts in shopping patterns actually increase or decrease consumers' overall expenditures. More specifically, we zoom in on three issues of interest. First, does the patronage of multiple stores lead consumers to spend less on groceries? Second, does this depend on the shopping organization, i.e. whether consumers visit these stores on separate or combined trips? Third, what is the role of store format choice? More specifically: how does the level of expenditures change when consumers patronize a hard-discounter store (like, for instance, Aldi or Lidl) instead of a traditional supermarket? To the best of our knowledge, though previous papers do provide valuable insights into the drivers of store choice, shopping pattern selection and spending, these questions have not been directly addressed. This is somewhat surprising, given that several scholars already suggested that some shopping pattern configurations may actually result in additional grocery spending – rather than a mere re-allocation of planned expenditures (Kahn and Schmittlein 1989). Our paper intends to further address this premise.

We start by outlining why and how alternative shopping patterns may affect consumer grocery spending, thereby building on the Motivation-Opportunity-Ability (MOA) framework (Batra and Ray 1986; MacInnis and Jaworsky 1989). Though our objective is not to separate out these processes and drivers empirically, they help to understand why certain outcomes occur. Next, we empirically document the relationship between shopping pattern dimensions (i.e. single versus multiple stores, separate versus combined trips, traditional supermarket versus hard-discounter) and monthly grocery spending. In so doing, we make sure to account for the spurious link caused by their common underlying drivers (i.e. characteristics affecting both shopping pattern choice and spending).

Our findings expand the current marketing literature in several ways. Previous research has uncovered a considerable number of factors that drive consumers' choice of shopping pattern (e.g. Cude and Morganosky 2001; Gijsbrechts et al. 2008; Krider and Weinberg 2000). Moreover, a few studies link shopping pattern characteristics to specific aspects of subsequent in-store purchase behavior, such as price and promotion sensitivity (Bell, Bucklin and Sismeiro 2000) and unplanned purchases (Bell, Corsten and Knox 2011; Inman, Winer and Ferraro 2009). Our results complement these insights, by documenting how shopping pattern choice affects consumers' overall (monthly) grocery spending. Our findings also add to the literature on consumer shopping behavior. By laying out the processes that influence spending under different shopping regimes, we add to previous research on the impact of household and environmental factors influencing consumer spending and their adherence to budget constraints (e.g. Van Ittersum et al. 2010).

The discussion is organized as follows. We first present the conceptual framework, in which we theorize on how consumers' shopping patterns may influence their grocery spending. Next, we present the methodology used to assess this relationship empirically, followed by a description of the data. We then discuss the estimation results and their implications. In the last section, we outline the limitations and issues for future research.

4.2 Theoretical Background

Households nowadays have access to an increasing number of grocery outlets and store formats, which – together with other evolutions such as increased mobility and information access – open up multiple ways to do their grocery shopping.[27] Faced with these options, households may engage in strategic behavior (Fox 2005), and develop systematic shopping patterns that allow them to meet their shopping objectives over a longer planning period (Gijsbrechts et al. 2008). Such shopping patterns can be characterized along three broad dimensions. First, consumers can buy the vast majority of their grocery purchases at a single store, or, conversely, allocate these purchases across multiple stores (Bell et al. 2000; Gijsbrechts et al. 2008). Second, when visiting multiple stores, consumers have different options to organize their trips to these stores: they can visit them either at separate points in time, or on chained (combined) shopping trips (e.g. Popkowski Leszczyc and Timmermans 2001). Third, consumers have to make a selection of which store format(s) to visit. From a spending point of view, the store format classification based on pricing strategy is particularly relevant (Bell and Lattin 1998). As such, and given the recent evolutions in the retailing landscape, we distinguish between traditional supermarkets, characterized by a HiLo strategy (high regular prices and frequent price promotions), and hard-discounters, which strongly focus on consistently low (EDLP) price levels (Cleeren et al. 2010).

The "traditional", most straightforward shopping pattern is for consumers to purchase the larger part of their groceries at a single traditional supermarket – their "preferred store" (Hoyer and MacInnis 2010). However, more often than not, consumers are found to deviate from this pattern – a major reason being to economize on grocery spending (and as such pay less for the same shopping basket, or be able to buy more with the same budget) (Fox and

[27] Another interesting development in this regard is that consumers also have the option to buy their groceries online. Online shopping environments offer consumers greater control over when and how long they shop, and in general allow for easier price comparisons and quicker store navigation. As is argued in the remainder of the theoretical section, these factors may strongly shape consumers' spending decisions. In this paper, however, we choose to focus on 'offline' shopping patterns only, given that the penetration of online grocery shopping is currently still very low: for example, only 2% of consumers in the Netherlands buys groceries online at a regular basis (i.e. at least once per month) (EFMI 2010).

Hoch 2005; Gauri et al. 2008). In the remainder of this section, we discuss how different shopping pattern dimensions may shape consumers' expenditures.

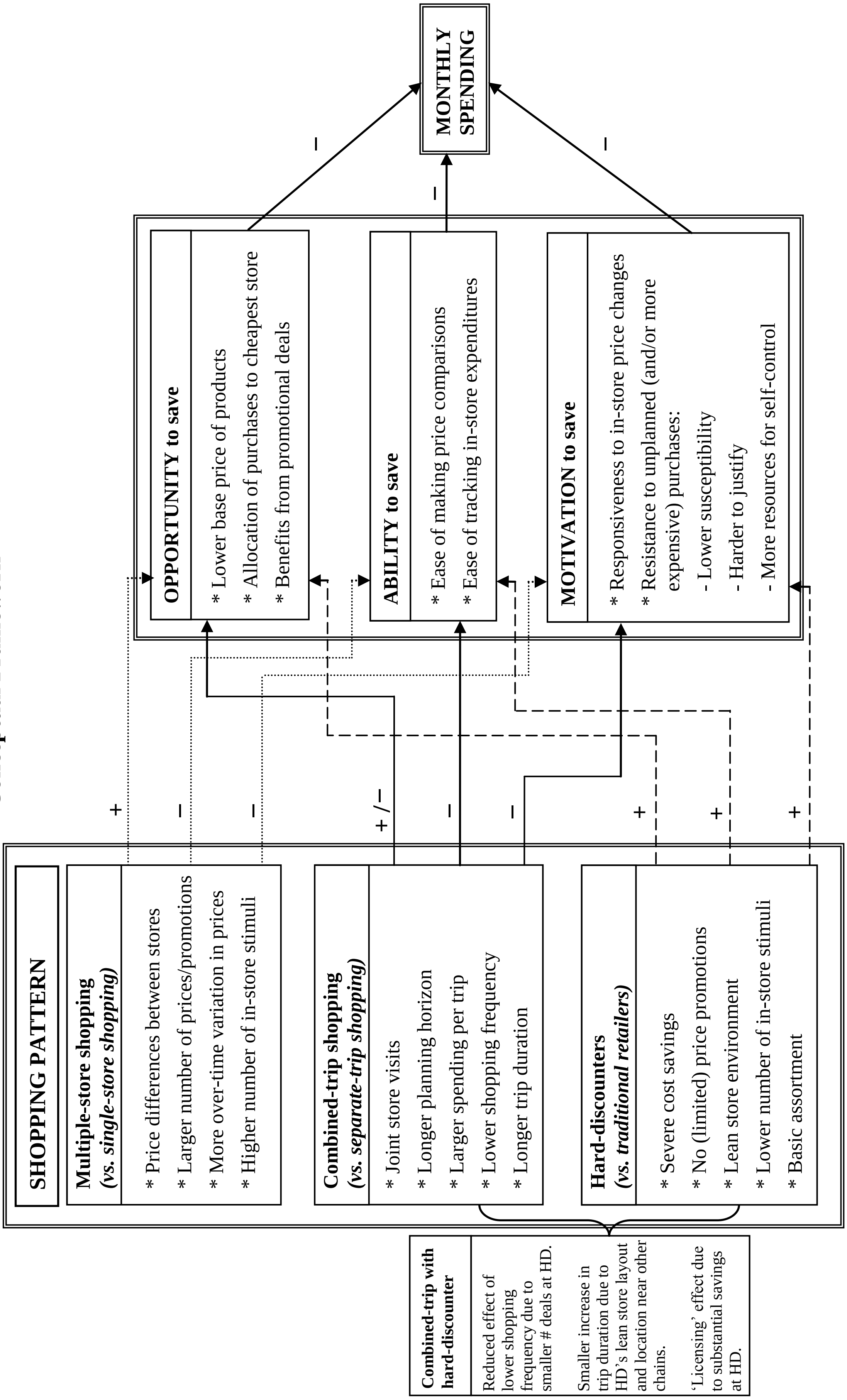
Our conceptualization, summarized in Figure 4.1, is rooted in the motivation-opportunity-ability framework proposed by Batra and Ray (1986). Alternative shopping patterns differ in the opportunities they offer to reduce grocery spending. However, they may also affect the consumers' ability to realize these savings and their motivation to stick to this objective. Below, we indicate how each of the different pattern dimensions (choice of single versus multiple stores, choice of shopping trip organization and choice of store format) can affect consumers' opportunity, ability and motivation to control spending – and what causes these effects.

Multiple-store (versus single-store) shopping

Consumers who systematically visit multiple stores have greater opportunities to buy their shopping basket at a lower cost. Provided that price differences exist between stores, they can take advantage of such differences by cross-shopping – buying each product in the store that sells it for the most attractive price. In addition, multiple-store shoppers will typically have access to a larger number of price promotions (than single-store shoppers), increasing the likelihood that they can buy a considerable amount of items on their shopping list at a reduced price. Hence, spreading grocery purchases over more than one store can lead to important savings (Gauri et al. 2008).

At the same time, however, patronizing multiple stores renders the process of price comparison and evaluation much more complex (Alba et al. 1994). Not only do consumers have to evaluate a larger set of product prices, price comparisons can also be complicated by (i) the separation of available price information in time and space, (ii) a larger (promotional) variation in prices, and (iii) lack of overlap in the stores' assortments. In such a case, given their limited processing resources, consumers may become "overloaded" and lose sight of the

FIGURE 4.1
Conceptual Framework



best available prices. In contrast to single-store shoppers, who can focus on within-store price comparisons for a smaller set of category items, multiple-store shoppers may thus be less able to spot and take advantage of interesting prices. This can make their savings over single-store shoppers less pronounced.

In addition, somewhat paradoxically, visiting multiple stores may dampen consumers' motivation to save, for two reasons. First, given that multiple-store shoppers already expect to save money by allocating their purchases across stores, they may feel less need to engage in further (in-store) price search for each item on their shopping list (Bell et al. 2000). This makes it less likely that these consumers respond to attractive price deals for the items they plan to buy. Second, as each store environment comes with its own purchase triggers (e.g. atmospheric stimuli, displays and/or in-store coupons), multiple-store shoppers may become more distracted from their savings goal. Confronted with a larger number of different "temptations", these consumers may engage in more unplanned purchases (Donovan et al. 1994; Heilman et al. 2002; Inman et al. 2009) – which reduces their savings over single-store shoppers.

In sum, while multiple-store shopping does give consumers access to better prices, the increased complexity of price comparisons and higher exposure to in-store marketing can negatively affect their ability and motivation to seize this saving opportunity. As such, consumers will not necessarily spend less money when they shop at multiple stores; on the contrary, they may spend even more.

Combined-trip (versus separate-trip) shopping

The way consumers organize shopping trips to different stores affects their opportunities for savings. On the one hand, combined shopping trips allow consumers to purchase each product at the preferred store for that product (Gijsbrechts et al. 2008). This is much more difficult in the case of separate store visits, however. Some categories are purchased on such a frequent basis (e.g. perishable products; Krider and Weinberg 2000) that consumers will need to buy them at virtually every store visit, regardless of whether the store is actually preferred for these categories. Hence, combined-trip patterns better reap the savings opportunities from cross-store price differences. On the other hand, however, being more spread in time, separate visits leave more room for capitalizing on temporary deals at each of the different stores (Gauri et al. 2008). Depending on whether cross-store or cross-time differences dominate, the opportunity to save will thus be higher for combined- or for separate-trip patterns.

Shopping organization may also influence consumers' ability to spot savings opportunities. Given that combined trips involve several store visits, they can be more cognitively demanding. Given the multitude of purchase decisions that have to be made on a typical grocery shopping trip, and the higher time pressure when visits to two different stores have to be combined, this may leave combined-trip shoppers less apt to compare prices and monitor spending than their separate-trip counterparts.

In a similar vein, consumers' motivation to focus on savings and stick to a strict shopping list may be affected. Three factors are at play here. First, combined trips entail more travel time (as consumers have to travel from store to store), a longer total checkout time, and a larger number of categories to be bought. This longer shopping trip duration can lead consumers to deplete their resources for self-control (Stilley, Inman and Wakefield 2010), which increases the likelihood that the consumer indulges in impulse purchases – and thereby spends more (Thomas and Garland 1993). Second, whereas separate-trip shoppers have more flexibility in aligning the timing of their trips with their moments of consumption, combined-trip shoppers have to plan further ahead. Following Ülkümen, Thomas and Morwitz (2008), this makes them feel less confident in setting a trip budget – which results in an upward adjustment of the budget. This additional "budget slack" (Stilley et al. 2010) may then be used to justify more unplanned or expensive purchases. Third, the outlay on combined patterns is less separated in time. Building on Thaler's (1985) mental accounting theory, this may make spendings on combined-trips more acceptable to consumers: single (integrated) losses being preferred over several smaller (segregated) losses that add up to the same amount (e.g. Heath, Chatterjee and France 1995; Mazumdar and Jun 1993). As a result, consumers may be less motivated to keep their losses in check (i.e. to save) on combined trips – again making it easier to justify additional or more expensive purchases.

In sum, while combined-trip patterns do not by definition provide more or less savings opportunities than separate-trip patterns, they do make it more difficult for consumers to spot such opportunities. Moreover, they are more likely to trigger additional (or more expensive) purchases – not only because consumers are more tempted, but also because they can better justify such purchases to themselves. It follows that consumers can be expected to spend more on combined-trip patterns than on separate-trip patterns.

Shopping patterns with (versus without) a hard-discounter

Hard-discounters differ from traditional supermarkets in their price and promotion strategy, as well as assortment and store management practices. To offer high quality products at bottom prices, hard-discounters cut costs by streamlining their operations, by stocking a limited assortment that mainly consists of private label products, and by maintaining a strictly functional, no-frills store organization (Steenkamp and Kumar 2009). Sales promotions or other in-store incentives are seldom used. Instead, hard-discounters' regular prices lie (on average) more than 60% (40%) below the regular (promotional) prices of national brands sold at traditional supermarkets (Nauwelaers et al. 2012; Nielsen 2007). Clearly, this allows consumers to cut down the overall cost of their shopping basket, and presents them with ample opportunity to realize savings. At the same time, the hard-discounter strategy may also influence their in-store spending in other ways.

For one, the hard-discounter’s lean assortment and consistently low prices lead to high price transparency and facilitate in-store price comparisons. This is in contrast with traditional (Hi-Lo) supermarkets, where the larger price variability complicates price search and evaluation (Vanhuele and Drèze 2002). Hard-discounter shoppers may therefore be better able to save money without too much effort, compared to traditional supermarket shoppers. In addition, due to the lack of in-store stimuli, shopping at a hard-discounter may be less cognitively taxing to a consumer. This may enable consumers to keep better track of their in-store expenditures (Van Ittersum et al. 2010), and help them stick to their budgets.

In addition, consumers shopping at hard-discounters may remain more motivated to behave consistently with their savings goal. First, since hard-discounters offer virtually no price deals (Nielsen 2007) or other in-store marketing incentives (such as in-store displays), they tend to stimulate less unplanned buying. In contrast, traditional supermarkets frequently offer temporary price promotions in multiple categories. This not only drives up purchases in the promoted category, but is also shown to elicit additional purchases in other categories (Drèze, Nisol and Vilcassim 2002; Walters 1991). Price promotions may provoke a consumer to spend more on non-promoted items because they enhance his shopping mood (Heilman et al. 2002; Milkman and Beshears 2009), or because the promotional savings are seen as “unexpected income”, which is readily spent on other purchases (Hodge and Mason 1995). Hence, the higher exposure to promotional incentives in traditional supermarkets may entice consumers to deviate from their savings goal, and spend more than they would in a “promotion-barren” hard-discounter store. Second, while traditional supermarkets’ use of atmospheric elements and in-store marketing may evoke a hedonic shopping orientation, the hard-discounter’s functional, no-frills store environment and back-to-basics assortment strategy (Cleeren et al. 2010) instead stimulates a utilitarian, goal-oriented shopping attitude (Arnold and Reynolds 2009; Babin and Darden 1995). This further reduces the consumers’ receptivity to in-store incentives and makes them more motivated to hold on to their purchase plans (Babin and Darden 1995).

All in all, consumers who include a hard-discounter in their shopping pattern have considerable opportunities to save money through the hard-discounter's overall low price level. In addition, they will be better able to spot these opportunities and keep track of their spending. Moreover, hard-discounter shoppers are less exposed (as well as less receptive) to in-store marketing incentives aimed to stimulate unplanned purchases. Not surprisingly, this leads one to expect that consumers' grocery spending will be lower when a hard-discounter is incorporated into their shopping pattern.

Interaction effects

Apart from the main effects discussed above, some interesting interactions can emerge between the shopping pattern dimensions. While hard-discounters are seldom selected as the sole (or even primary) store, they are quite predominant in multiple-store patterns (Gijsbrechts et al. 2008), and more easily give rise to a combined-trip organization (see also chapter 2 of this dissertation). An interesting question is then: for shopping patterns involving a traditional store and a hard-discounter, does a combined-trip pattern also entail higher spending than a separate-trip pattern? Different, opposing, forces may be at work here.

On the one hand, for patterns including a traditional and a hard-discounter store, savings opportunities stem not so much from over-time variation in price promotions (since hard-discounters generally hold their prices stable over time), but more from cross-format price differences. This substantially reduces – or even removes – the savings opportunities that are offered by separate-trip patterns over combined-trip patterns (due to being more spread in time). Conversely, the advantage of combined-trips over separate-trips in terms of saving opportunities – households being able to buy every product category in the store with the best offer – still applies. Moreover, as hard-discounters tend to be small and often located near complementary traditional supermarkets (as is discussed in chapter 2 of this dissertation), the shopping time for chained visits can be substantially lower, and closer to that of separate visits. This, together with the fact that a hard-discounter's lean store environment is less cognitively taxing, is likely to bring combined-trip shoppers closer to separate-trip shoppers in terms of their motivation and ability to save. Taken together, this implies that combined-trip shoppers may actually spend less than separate-trip shoppers when a hard-discounter is incorporated into their shopping patterns –.having sufficient motivation and ability to take advantage of the larger saving opportunities in these patterns.

On the other hand, however, much like (promotional) savings on planned items may induce spending on unplanned items (Hodge and Mason 1995), visiting a hard-discounter may provide consumers with a "license" to spend more at the traditional store. This will particularly hold for combined visits, in which the savings perception of hard-discounter shopping and the opportunity to indulge at the traditional supermarket, co-occur on the same trip. Under this premise, combined-trip shoppers may fail to capitalize on the savings opportunities that are available within their specific shopping pattern – and still spend more in the end than separate-trip shoppers.

In conclusion, whether a consumer spends more in combined- than in separate-trip patterns possibly depends on whether a hard-discounter is incorporated into these patterns. To shed more light on this issue, we will present a methodology below that allows us to assess the actual nature of this interaction – as well as of the other effects discussed in this section.

4.3 Methodology

As outlined above, rather than focusing on trip-to-trip behavior, we are interested in consumers' stable (strategic) shopping patterns and, in particular, how these relate to their total grocery spending. Consistent with this focus, we take the household-month as our unit of analysis, and track consumers' shopping patterns and grocery spending levels on a monthly basis. In line with our conceptualization, we distinguish between shopping patterns that (i) do or do not involve a hard-discounter, and (ii) do or do not include multiple stores. Moreover, within the multiple-store patterns, we (iii) distinguish between separate- and combined-trip organizations. This leads to a total of six shopping patterns (for details on the operationalization: see the next section and Table 4.1).

A straightforward procedure would be to simply test for differences in average spending across these shopping pattern alternatives. Such an approach, however, would ignore two important issues. First, it is clear that spending levels are not dictated by shopping patterns alone, but may also strongly differ across households (e.g. Bawa and Ghosh 1999). Hence, to capture the "true" effect of shopping patterns on consumer spending, we need to control for heterogeneity in spending across consumers, along with other possible confounds like seasonality. Second, the observed shopping patterns may be endogenous – shopping patterns themselves possibly depending on the households' characteristics and associated grocery budgets (Bell and Lattin 1998; Fox and Hoch 2005). To accommodate this endogeneity, we incorporate an additional model layer (estimated simultaneously) in which consumers' choice of shopping pattern is explained by a number of variables – including observed household features. In addition, we allow the error terms of the main spending equation and the pattern choice equation to be correlated. This enables us to capture effects of unobserved variables that simultaneously affect pattern choice and spending. Our spending [4.1] and pattern choice [4.2] equations take the following form:

[4.1] $N\_Spending_{h,t} = N\_Spending^{*}_{h,t} + \varepsilon_{h,t}$, with:

$$\begin{aligned} N\_Spending^{*}_{h,t} = \beta_0 &+ \gamma * N\_Spending_{h,t-1} + \beta_1 * SSS\_HD_{h,t} \\ &+ \beta_2 * MSS\_SEP\_NOHD_{h,t} + \beta_3 * MSS\_SEP\_HD_{h,t} \\ &+ \beta_4 * MSS\_CMB\_NOHD_{h,t} + \beta_5 * MSS\_CMB\_HD_{h,t} \\ &+ \sum_l \delta_l * D_{l,h} + \varphi_1 * Summer_t + \varphi_2 * Winter_t + \varphi_3 * Month_t \end{aligned}$$

[4.2] $P_{h,t}(s) = \dfrac{e^{U_{h,t}(s)}}{\sum_p^P e^{U_{h,t}(p)}}$, with:

$U'_{h,t}(s) = U_{h,t}(s) + \eta_{h,t}(s)$, and:

$$\begin{aligned} U_{h,t}(s) = \lambda_s &+ \psi * Pattern_{h,t-1}(s) + \sum_l \theta_{l,s} * D_{l,h} + \zeta_{1,s} * Summer_t + \zeta_{2,s} * Winter_t \\ &+ \xi_{1,s} * Upscale_{h,t} + \xi_{2,s} * Value_{h,t} + \xi_{3,s} * HD_{h,t} + \xi_{4,s} * (Upscale_{h,t} * Value_{h,t}) \\ &+ \xi_{5,s} * (Upscale_{h,t} * HD_{h,t}) + \xi_{6,s} * (Value_{h,t} * HD_{h,t}) + \xi_{7,s} MinDist_{h,t} \end{aligned}$$

We elaborate on the variables included in these two equations below.

Spending equation

The dependent variable $N\_Spending_{h,t}$ reflects the total amount of money that was spent on groceries by household *h* in month *t*, divided by the household's average monthly spending. We use this "normalized" dependent variable because it allows us to control for heterogeneity in grocery spending across households. As such, the dependent variable should be interpreted as the household's "relative" spending (i.e. the ratio of actual to average monthly spending) – indicating whether the consumer spent more, less, or the same as the average amount. The lagged spending variable ($N\_Spending_{h,t-1}$) is constructed in the same fashion, and is included to accommodate for possible dynamic effects. To control for seasonality in consumer spending (e.g. during holiday periods, or due to weather effects (Block and Morwitz 1999; Murray et al. 2010)), we include two dummies: $Summer_t$ and $Winter_t$. Moreover, $Month_t$ captures any exogenous trends in consumer spending that may have occurred over time. The shopping pattern effects that are key to our study (savings opportunity, ability and motivation) are captured through the variables $SSS\_HD_{h,t}$, $MSS\_SEP\_NOHD_{h,t}$, $MSS\_SEP\_HD_{h,t}$, $MSS\_CMB\_NOHD_{h,t}$ and $MSS\_CMB\_HD_{h,t}$, which indicate the shopping pattern that is chosen by household *h* in month *t*. These five dummies correspond to the six different shopping patterns as mentioned at the beginning of this section, with the single-store, no hard-discounter pattern as the reference condition.

Shopping pattern choice equation

The shopping pattern choice equation [4.2] is specified as a multinomial logit model, with a separate set of parameters for each shopping pattern.[28] The dependent variable, $P_{h,t}(s)$, is the probability that in month *t*, household *h* selects shopping pattern *s* from a set of *P* possible shopping patterns (where *P* includes the same six patterns that were mentioned in the previous paragraph). $U_{h,t}(s)$ and $\eta_{h,t}(s)$ are the systematic and (Gumbel-distributed) random components of utility, respectively.

We again use previous household (choice) behavior ($Pattern_{h,t-1}(s)$) as an explanatory variable in the model, to accommodate for the fact that households often make choices based on past decisions. In addition, we include household demographics ($D_{l,h}$) and seasonal dummies ($Summer_t$ and $Winter_t$), as both of these sets of variables may affect the time available for grocery shopping – which in turn influences shopping pattern choice (e.g. Fox and Hoch 2005; Popkowski Leszczyc and Timmermans 1997). The remaining variables pertain to the composition of a household's local store environment. First, consumers' inclusion of store formats in their shopping pattern will naturally depend on the availability of these formats. We therefore include the variables $Upscale_{h,t}$, $Value_{h,t}$ and $HD_{h,t}$, reflecting

[28] We keep all parameters fixed to zero for the single-store, no hard-discounter shopping pattern to ensure identification.

the number of "upscale" traditional, value-oriented traditional, and hard-discounter chains present in the households' local environment. We also add interactions between these variables, as these may drive the prevalence of multiple-store patterns involving combinations of these formats.[29] The variable $MinDist_{h,t}$ is the smallest travel distance between any two stores in household *h*'s local store environment in *t*. It reflects the extent to which stores in the vicinity of the household are "clustered", which strongly determines the attractiveness of combined-trip shopping patterns (e.g. Fox and Hoch 2005; Popkowski Leszczyc et al. 2004). Though these variables are unlikely to determine the household's level of grocery spending directly, they can drive the availability and attractiveness of different shopping patterns, and therefore enter equation [4.2].

As mentioned before, we estimate the spending and shopping pattern choice equations simultaneously, and allow their error terms ($\varepsilon_{h,t}$ and $\eta_{h,t}(s)$) to be correlated. To achieve this, we follow an approach proposed by Zhang and Krishnamurthi (2004), and assume that the error of the spending equation, and the transformed error of the pattern choice equation, follow a bivariate logistic distribution (see Zhang and Krishnamurthi 2004 for more details). This results in the following joint probability that household *h* adopts shopping pattern *s*, and spends $N\_Spending_{h,t}$, in month *t* (Zhang and Krishnamurthi 2004):

$$P_{h,t}(s; N\_Spending_{h,t}) = \frac{e^{U_{h,t}(s)}}{\sum_{p}^{P} e^{U_{h,t}(p)}} * \frac{\varsigma * e^{\varsigma(N\_Spending^{*}_{h,t} - N\_Spending_{h,t})}}{[1 + e^{\varsigma(N\_Spending^{*}_{h,t} - N\_Spending_{h,t})}]^2} *$$

$$[4.3] \quad [1 + \chi(1 - \frac{e^{U_{h,t}(s)}}{\sum_{p}^{P} e^{U_{h,t}(p)}}) * \frac{-1 + e^{\varsigma(N\_Spending^{*}_{h,t} - N\_Spending_{h,t})}}{1 + e^{\varsigma(N\_Spending^{*}_{h,t} - N\_Spending_{h,t})}}],$$

[29] An important driver of multiple-store shopping is complementarity between available stores (Gijsbrechts et al. 2008). Such complementarities are substantial for hard-discounters and upscale traditional supermarkets, while hard-discounters and value-oriented traditional chains are less complementary (see chapter 2 of this dissertation). The interactions between the store chain variables allow us to capture these differential complementarities between the store formats accessible to the household.

where χ captures the interdependence between the spending and pattern choice equations' errors, and ς is a scale parameter. Accordingly, we maximize the following log-likelihood:

$$[4.4] \quad \ln \prod_h \prod_t \prod_s P_{h,t}(s; N\_Spending_{h,t})^{y_{h,t}(s)}$$

where $y_{h,t}(s)$ is an indicator variable that reflects household h's actual choice of shopping pattern in month t. We estimate the parameters using simulated maximum likelihood.

4.4 Data and Operationalizations

Data sources

Our main data source consists of household scanner panel data for the Dutch market, as provided by GfK for the period January 2002 – August 2006. From this data set, we can derive both households' choice of shopping patterns and their monthly grocery expenditures. It also contains information on various household characteristics, including their socio-demographic attributes and geographical location. To characterize households' local store environment (such as the stores that are available and the distances between them) we use data from Reed Business that tracks, every three to four months, the geographical location of all Dutch grocery outlets.

We focus on household purchases made in the top 9 grocery chains in the Netherlands, thereby covering 78% of sales. Our sample includes all households that participated in the panel throughout the entire period between January 2002 and August 2006, and bought more than 80% of their groceries in the nine chains under study. To ensure that the expenditures of these households are comparable across different shopping patterns, we only consider purchases made in categories that are available across all nine chains (319 categories, which account for 84% of grocery spending). Our final sample thus covers 1325 households, observed over 56 months.

Operationalizations

Table 4.1 describes how we operationalize the dependent and independent variables of our model. We will now further discuss some of the key variables below.

TABLE 4.1
Variable Operationalizations

Notation	Variable name	Operationalization
Dependent variable		
$N\_Spending_{h,t}$	*Normalized household grocery spending*	$\dfrac{Spending_{h,t}}{\frac{1}{T}\sum_{t=1}^{T} Spending_{h,t}}$
$Spending_{h,t}$	*Household grocery spending*	Total amount of money spent on groceries by household *h* in month *t* (in hundreds of euros).
Shopping patterns		
$SSS\_HD_{h,t}$	*Single-store shopping with hard-discounter*	Step dummy, 1 when household *h*'s shopping pattern in month *t* is single-store and includes a hard-discounter, 0 otherwise.
$MSS\_SEP\_NOHD_{h,t}$	*Separate-trip multiple-store shopping without hard-discounter*	Step dummy, 1 when household *h*'s shopping pattern in month *t* is multiple-store, involves separate trips and does not include a hard-discounter, 0 otherwise.
$MSS\_SEP\_HD_{h,t}$	*Separate-trip multiple-store shopping with hard-discounter*	Step dummy, 1 when household *h*'s shopping pattern in month *t* is multiple-store, involves separate trips and includes a hard-discounter, 0 otherwise.
$MSS\_CMB\_NOHD_{h,t}$	*Combined-trip multiple-store shopping without hard-discounter*	Step dummy, 1 when household *h*'s shopping pattern in month *t* is multiple-store, involves combined trips and does not include a hard-discounter, 0 otherwise.
$MSS\_CMB\_HD_{h,t}$	*Combined-trip multiple-store shopping with hard-discounter*	Step dummy, 1 when household *h*'s shopping pattern in month *t* is multiple-store, involves combined trips and includes a hard-discounter, 0 otherwise.
$Pattern_{h,t}(s)$	*Household pattern choice*	Dummy indicator, equals 1 if household *h* engaged in shopping pattern *s* in month *t*, 0 otherwise.
Controls: Household demographics		
$HHsize_h$	*Household size*	Number of household members of household *h*
$Children_h$	*Number of children*	Number of child members (age<18) of household *h*
$Income_h$	*Household income*	Net monthly income (in hundreds of euros) of household *h*
$DualInc_h$	*Dual-income household*	Dummy indicator, equals 1 if household *h* is a dual-income household, 0 otherwise
Age_h	*Age of household head*	Age (in years) of the head of household *h*
Controls: Seasonality		
$Summer_t$	*Summer indicator*	Step dummy, 1 when month *t* is in June, July or August, 0 otherwise.
$Winter_t$	*Winter indicator*	Step dummy, 1 when month *t* is in December or January, 0 otherwise.
Controls: Store environment		
$Upscale_{h,t}$ $Value_{h,t}$ $HD_{h,t}$	*Number of upscale, value-oriented and hard-discounter stores*	Number of "upscale" (Albert Heijn, C1000, Super de Boer), "value-oriented" (Dirk, Edah, Jumbo, Plus)[a] and "hard-discounter" (Aldi, Lidl) chains that have an outlet located less than 5 km away from household *h* in month *t*.
$MinDist_{h,t}$	*Minimum inter-store distance*	Smallest observed distance between any two chains that are located less than 5 km away from household *h* in month *t*.

[a] Our distinction between upscale and value-oriented (traditional) chains is based on the pattern of inter-store complementarities in chapter 2 of this dissertation, where the three chains classified as upscale were found to be much more complementary to hard-discounters than the four chains classified as value-oriented.

We measure a household's grocery expenditure in a given month as the total amount spent in that month within the 9 chains and 319 categories under study. If more than 80% of this amount was spent in a single chain, the household's shopping pattern for that month is classified as "single-store"; in all other instances, it is defined as "multiple-store". In the latter case, the shopping pattern is "combined-trip" when more than half of the household's expenditures were made on multi-store trips, and "separate-trip" otherwise.[30] Finally, we categorize a pattern as "with hard-discounter" if a hard-discounter chain (in our data: Aldi or Lidl) is either the household's primary or secondary store for that month (in terms of spending), and as "without hard-discounter" otherwise. These operationalizations are similar to previous studies (Gijsbrechts et al. 2008).

Data descriptives

Table 4.2 displays, for each shopping pattern, the frequency with which it occurs, as well as the average amount of money spent by households within the pattern. Several interesting observations can be made. First, consumers commonly visit multiple stores – about 56% of shopping patterns are classified as such – and do so primarily by making separate trips to each store. While hard-discounters are often incorporated within multiple-store patterns, they are rarely visited in isolation. Combined-shopping patterns are much less prevalent than separate-trip patterns, but relatively more prominent if the pattern involves a hard-discounter store.

Second, from the raw data in Table 4.2, it seems that compared to single-store shopping at a traditional supermarket, multiple-store shopping does not seem to yield substantial savings: average expenses only being lower for separate-trip patterns that include a hard-discounter. To the contrary: when only traditional supermarkets are visited, multiple-

[30] Similar to chapter 2, multi-store trips are operationalized as trips where more than one chain was visited on the same part of the day (morning, afternoon or evening).

store shopping appears to be associated with higher spending – especially when the stores are visited on combined trips. This spending increase, however, cannot simply be attributed to the shopping pattern as such. Rather, it may reflect that households with different spending propensities also shop in a different way. We will therefore present the estimation results of our model in the next section, as it allows us to disentangle these effects.

TABLE 4.2
Shopping Patterns and Household Expenditures

Shopping pattern	Relative frequency	Average grocery spending (euros)
Single-store, without hard-discounter	41.2%	176.74
Single-store, with hard-discounter	2.4%	101.46
Separate-trip multiple-store, without hard-discounter	22.2%	184.80
Separate-trip multiple-store, with hard-discounter	22.4%	170.37
Combined-trip multiple-store, without hard-discounter	4.2%	193.95
Combined-trip multiple-store, with hard-discounter	7.6%	180.35

4.5 Results

Our model comprises two (simultaneously estimated) equations: a shopping-pattern choice and a spending equation. Because the shopping-pattern choice equation is mainly included to avoid endogeneity bias, we only briefly comment on its parameter estimates. The main part of this section is devoted to the results for the spending equation – along with their implications for consumer expenditures across different shopping patterns.

Shopping pattern choice equation

Table 4.3 displays the estimates for the shopping-pattern choice equation. The parameters make intuitive sense. The coefficient for lagged pattern choice is positive and highly significant – confirming previous literature that there is inertia in households' shopping patterns over time (Gijsbrechts et al. 2008). For the remaining variables (whose values are not

TABLE 4.3
Parameter Estimates (Shopping Pattern Choice Equation)

Parameter		**SSS No HD**	**SSS HD**	**Separate MSS No HD**	**Separate MSS HD**	**Combined MSS No HD**	**Combined MSS HD**
Intercept	(λ_s)		**-1.697**	**-.426**	**.591**	**-1.581**	**-.239**
			(-9.406)	(-6.832)	(6.697)	(-12.940)	(-2.582)
Lagged pattern choice	(ψ)	**2.042**[a]	**2.042**	**2.042**	**2.042**	**2.042**	**2.042**
		(617.042)	(617.042)	(617.042)	(617.042)	(617.042)	(617.042)
Household demographics							
Household size	($\theta_{1,s}$)		**.465**	**.131**	**.342**	**.343**	**.472**
			(37.154)	(16.247)	(41.706)	(32.520)	(46.588)
Number of children	($\theta_{2,s}$)		**-.160**	**-.099**	**-.139**	**-.410**	**-.299**
			(-8.417)	(-8.442)	(-12.147)	(-24.767)	(-22.083)
Income	($\theta_{3,s}$)		**-.038**	**-.010**	**-.032**	**-.006**	**-.031**
			(-24.110)	(-11.283)	(-33.824)	(-4.883)	(-27.101)
Dual-income	($\theta_{4,s}$)		**-.300**	-.045	**-.227**	**-.226**	**-.738**
			(-4.456)	(-1.067)	(-5.646)	(-4.264)	(-6.549)
Age	($\theta_{5,s}$)		**.010**	**-.004**	**.007**	**-.005**	.000
			(10.548)	(-7.454)	(11.705)	(-5.862)	(.673)
Seasonality							
Summer	($\zeta_{1,s}$)		.134	.035	.043	-.034	-.017
			(1.285)	(.814)	(.842)	(-.464)	(-.247)
Winter	($\zeta_{2,s}$)		-.106	.027	-.042	.019	-.008
			(-.773)	(.572)	(-.773)	(.201)	(-100)
Store environment							
#Upscale supermarkets	($\xi_{1,s}$)		**.132**	.011	**-.296**	*-.087*	**-.103**
			(1.983)	(.458)	(-8.616)	(-1.871)	(-3.071)
#Value supermarkets	($\xi_{2,s}$)		**-.952**	**.070**	**-.483**	*.091*	**-.380**
			(-10.755)	(2.242)	(-12.249)	(1.752)	(-8.745)
#Hard-discounters	($\xi_{3,s}$)		.080	**-.251**	**-.359**	-.005	-.091
			(.799)	(-6.971)	(-6.152)	(-.077)	(-1.330)
#Upscale * #Value	($\xi_{4,s}$)		**.152**	*-.020*	**.100**	.011	.020
			(6.009)	(-1.704)	(8.060)	(.577)	(1.507)
#Upscale * #HD	($\xi_{5,s}$)		**-.114**	**.071**	**.162**	**.055**	-.017
			(-2.994)	(5.457)	(7.156)	(2.072)	(-.675)
#Value * #HD	($\xi_{6,s}$)		**.236**	**.052**	**.064**	-.004	**.145**
			(9.569)	(4.625)	(4.197)	(-.205)	(7.329)
Minimum inter-store distance	($\xi_{7,s}$)		-.028	**-.048**	**-.166**	**-.218**	**-.601**
			(-.681)	(-4.136)	(-11.894)	(-10.576)	(-32.594)

[a] Estimates significant at the 5% (10%) level (two-sided) are portrayed in bold (italics). Values in brackets represent t-values for the coefficients.

shopping pattern-specific) the single-store, no hard-discounter pattern constitutes the reference alternative, such that the parameter estimates reflect differential effects relative to this alternative. Larger households and/or households with older (e.g. retired) members are more prone to incorporate a hard-discounter into their shopping pattern – probably because they are on a tighter budget. Similarly, low-income households have far stronger propensities to (also) shop at a hard-discounter format. Presence of more children especially decreases the likelihood of combined-trip patterns, which may reflect that it is more difficult for households with (young) children to leave the house for longer periods of time. Dual-earner households strongly prefer to visit a single (well-stocked) traditional supermarket for all of their grocery needs, which fits with their lower time availability for grocery shopping. While shopping pattern preferences thus greatly vary between households, we find them to remain relatively stable throughout the year – as none of the seasonality dummies is significant. Stronger presence of traditional (especially value-) supermarkets leads to more single-store and/or traditional-format shopping or, in the presence of many hard-discounter stores, to more multiple-store shopping involving both the traditional and hard-discounter format. Finally, as expected, lower inter-store distance makes households more likely to engage in combined-trip patterns.

Spending equation

Before turning to our prime parameters of interest (i.e. the shopping pattern parameters), we briefly review the effects for the control variables. Table 4.4 summarizes our results. Again, we find a significant positive effect of the lagged dependent variable, which may indicate that households' previous expenditures help them set their budgets for future periods. In addition, our results show that households spend significantly more during the summer and (especially) the winter holiday periods. Finally, we also find a downward trend in household spending over time, which corresponds to the notion that households increasingly seek good value-for-money (e.g. Nielsen 2008).

The shopping pattern parameters can be interpreted as average deviations between consumers' monthly spending in the reference shopping pattern (single-store shopping without hard-discounters) on one hand, and the five alternative patterns on the other. We now interpret these parameters, and discuss their implications.

TABLE 4.4
Parameter Estimates (Spending Equation)

Parameter			Parameter		
Intercept	(β_0)	**.780**[a]	***Shopping patterns***		
		(244.614)	Single-store,		(reference)
Lagged spending	(γ)	**.227**	without hard-discounter		
		(140.797)	Single-store,	(β_1)	**-.106**
Seasonality and trends			with hard-discounter		(-30.513)
Summer	(φ_1)	**.012**	Separate-trip multiple-store,	(β_2)	**.026**
		(6.030)	without hard-discounter		(12.007)
Winter	(φ_2)	**.034**	Separate-trip multiple-store,	(β_3)	**.016**
		(10.985)	with hard-discounter		(7.187)
Monthly trend	(φ_3)	**-.001**	Combined-trip multiple-store,	(β_4)	**.052**
		(-28.358)	without hard-discounter		(10.389)
Error interdependence with pattern choice			Combined-trip multiple-store,	(β_5)	**.048**
Error interdependence	(τ^{b})	**-.457**	with hard-discounter		(14.034)
		(-25.562)			
Scaling parameter	(ς)	**6.826**			
		(729.331)			

[a] Estimates significant at the 5% (10%) level (two-sided) are portrayed in bold (italics). Values in brackets represent t-values for the coefficients.
[b] To ensure that the estimate of the error interdependence parameter (χ) falls between -1 and 1, we used χ=2/exp(τ+1)-1 in our estimation procedure, and thus report the parameter estimate and t-value of τ here.

Zooming in first on the shopping patterns that do not incorporate a hard-discounter, we find that the parameters β_2 (multiple-store, separate-trips) and β_4 (multiple-store, combined-trips) are both positive and significant. This indicates that consumers shopping at traditional supermarkets, spend more in multiple-store patterns than they do in single-store patterns. Turning back to our theoretical framework, it thus seems that while consumers have the opportunity to save money when shopping at multiple-stores, they do not seem to realize this savings potential – on the contrary, they turn out to spend even more. In addition, parameter β_4 is larger in size than β_2, and a statistical test reveals that this parameter difference ($\beta_4 - \beta_2$) is indeed significant (p-value <.01). This implies that, as expected, multiple-store shoppers (at traditional supermarkets) spend more in combined-trip patterns than in separate-trip patterns.

Turning to the shopping patterns that include a hard-discounter; β_1 (single-store), β_3 (multiple-store, separate trips) and β_5 (multiple-store, combined-trips), we find further support for the above conclusions. The parameter differences ($\beta_3 - \beta_1$) and ($\beta_5 - \beta_1$) are significant (p-values <.01), and again indicate that more is spent on multiple-store than on single-store patterns. Moreover, we again find that expenditures are higher under combined-trip patterns than under separate-trip patterns (with the parameter difference ($\beta_5 - \beta_3$) being significant at p-value <.01). While we proposed that if the shopping pattern includes a hard-discounter, the inverse could hold as well, evidence for this claim thus remains lacking.

Based on our theoretical framework, we also expected that when consumers incorporate a hard-discounter into their shopping pattern, they will spend less on their groceries. While the estimated spending differences β_1, ($\beta_3 - \beta_2$) and ($\beta_5 - \beta_4$) are all in the right direction, we (somewhat surprisingly) find that they are only significant for single-store and separate-trip patterns (p-values <.01), but not for combined-trip patterns (p-value .45). Even though we theorized that when consumers incorporate a hard-discounter into their shopping pattern, their opportunity, ability and motivation to save money increases, the above result suggests that when the hard-discounter is visited on the same trips as other stores, total grocery spending does not go down. Our theoretical framework provided a possible explanation: when consumers know that money will be saved during their shopping trip because of a visit to the hard-discounter, they may perceive this as a “license to indulge” on that same shopping trip. They may, for instance, allow themselves to buy more expensive items at the traditional supermarket – which cancels out their savings.

To summarize, our findings indicate that, as expected, consumers spend more in multiple-store shopping patterns than in single-store patterns, and that this difference becomes especially pronounced when the stores are visited together on combined trips. While in the majority of cases, expenditures become lower again when consumers replace a traditional supermarket with a hard-discounter – we find, somewhat surprisingly, that this does not hold true when the consumers use combined trips to visit their stores-of-choice. Taken together, this leads to some interesting insights. First, even though consumers often decide to visit an additional supermarket (next to their main, traditional store) out of a desire to save on grocery expenses, we find that they actually spend more – even when the additional supermarket is a hard-discounter (see Table 4.4). Hence, despite the savings opportunities it creates, multiple-store shopping does not lead consumers to save on their actual grocery expenses. Second, we find that especially combined-trip patterns seem ill-suited to keep expenses in check. In these patterns, consumers' grocery outlay turns out to be the highest, and not even the incorporation of a hard-discounter helps to reduce spending.

4.6 Discussion

Today's consumers can do their grocery shopping in a variety of ways. Not only can they choose to visit formats other than the "traditional" supermarket (such as the hard-discounter); they can also decide to shop in more than one store – either by visiting them on separate occasions or on combined, multi-store trips. Engaging in such alternative shopping patterns provides consumers with an opportunity to save money. Hard-discounters, for example, offer quality products at much lower prices than traditional supermarkets, while the patronage of multiple stores allows consumers to exploit cross-store price differences. As indicated by Gauri et al. 2008 and Fox and Hoch 2005, judicious shopping-pattern choice thus holds the promise of sizeable cuts on grocery spending.

However, these same shopping patterns also strongly affect the consumers' shopping process and experience, e.g. with respect to the number of in-store stimuli that are encountered, the variety of different products that is available, and the length and frequency of shopping trips. These differences will, in turn, influence the extent to which consumers are able and/or motivated to capitalize on the saving opportunities associated with their shopping pattern. Following up on this premise, we proposed a framework on how different "dimensions" of shopping patterns may affect consumers' opportunity, ability and/or motivation to save on groceries and, in turn, their actual spending. In addition, we empirically document these effects by studying differences in consumers' monthly grocery spending across different shopping patterns, after accommodating for household differences and common unobservable drivers.

Interestingly, we find that, compared to a "standard" scenario where a consumer primarily shops at one traditional supermarket, consumers only end up spending less when they visit a single hard-discounter instead. Multiple-store shopping patterns, in contrast, drive up consumer expenses. Hence, this casts doubt on whether shopping around, in the end, leads consumers to cut down on their monthly grocery budgets – an objective that is commonly pursued (Nielsen 2011).

Furthermore, additional spending in multiple-store patterns becomes especially pronounced when the stores are jointly visited on combined trips. This type of shopping pattern thus seems particularly unsuitable for consumers who seek to capitalize on any savings opportunities that may exist across stores. Not even the inclusion of a hard-discounter helps to reduce expenses in these combined-trip patterns, suggesting that consumers use the savings at this format to justify more expensive purchases elsewhere.

Implications for consumer welfare and retail management

Our study generates valuable insights on the impact of shopping patterns on consumer welfare and retail performance. From a consumer perspective we find that, compared to a "standard" shopping pattern involving a single traditional store, the selection of an alternative shopping pattern seldom results in savings on grocery expenses. In fact, solely visiting a hard-discounter appears to be the only effective approach to achieve spending cuts. However, this is also the least chosen option by consumers – as hard-discounters carry only the most essential items in each category, and few national brands.

Though spreading purchases across multiple traditional stores also offers the potential to lower expenditures, we find that consumers, instead, end up spending more – possibly because the cross-store price differences are too small to compensate for consumers' reduced ability and motivation to save. Our findings further indicate that the risk of increased (rather than reduced) spending is especially high when consumers visit multiple stores on chained trips. Because these trips are more cognitively demanding and often made under time pressure, consumers can find it harder, and may be less motivated, to compare prices. At the same time, the increased exposure to in-store incentives may reduce the consumers' resistance to make unplanned purchases, resulting in higher expenditures on combined shopping trips – regardless of whether a cheaper hard-discounter is involved. Of course, to assess whether consumers would be better off avoiding these combined shopping trips, their advantages – such as reduced travel costs compared to separate trips – also have to be taken into account.

Even though consumers spend more in multiple-store patterns than in single-store patterns, retail managers naturally prefer consumers to visit their store in isolation, to procure their entire basket. However, we show that if a consumer visits the store together with other stores – the dominant pattern nowadays – more is spent if these stores are jointly visited on the same trip. This can be valuable information for retailers deciding on where to locate a new outlet. To illustrate, when entering a local market where multiple-store shopping prevails, retailers may be better off when their new outlet is located in the near vicinity of incumbent stores. Such a "twin-location" will strongly encourage multiple-store shoppers to visit the outlet on combined trips – thereby increasing the amount of money spent at the outlet. The finding that stores may benefit from a location close to their competitors is not new. However, our study puts it into a different perspective – co-location enticing shared customers to spend more. For traditional grocery stores, the results further suggest that investing in a pleasant store atmosphere and using in-store incentives to stimulate unplanned buying can prove particularly valuable in times of hard-discounter competition and declining store loyalty. Not only does it increase their share of household expenditures, it also enhances the overall spending by consumers (in their store).

4.7 Limitations and Future Research

Clearly, though our analysis leads to novel insights, it is also subject to limitations, and paves the way for future research. First, though savings are a key motive for consumers to patronize multiple stores (EFMI and CBL 2010), other motivations for multiple-store shopping may exist, and at least partly explain why no or little money is saved in the end. A consumer may, for example, choose to save money in some categories, but only because it allows him to spend more in others (Costa et al. 2006). Alternatively, a consumer may shop at multiple stores to ensure that he can buy his favorite item in every category (Cude and Morganosky 2001): a strategy that does not necessarily lead to lower spendings either. Future studies may therefore consider a more detailed distinction between the various shopping motivations (e.g. through qualitative surveys and/or a latent class approach) – and study how these motivations affect what consumers spend across different shopping patterns.

Second, while we uncovered interesting differences in consumer spending across shopping patterns, and theorized on factors that may drive these differences (e.g. difficulty of price comparisons, unplanned purchases and inaccuracies in tracking of expenditures), our current analysis did not allow us to assess the relative impact of each of these factors. Such information, however, might guide store managers on how to effectively stimulate consumer spending across different shopping patterns. We leave it as an issue for future study.

Third, our current model takes a fairly "static" view on how shopping patterns may drive consumer spending. That is, we only focus on how households' expenditures are affected by their current shopping pattern. However, it is also plausible that spending decisions may (partially) result from past pattern choices as well. For example, after making a lot of extra purchases in a (combined) multiple-store pattern (e.g. because of impulse buying and/or stockpiling behavior), a household may choose to deplete this additional inventory first – and as such restrict its spending in subsequent periods. To uncover whether such longer-term effects indeed exist, future studies can adopt a more "dynamic" perspective on the relationship between shopping patterns and spending.

Fourth, our conceptualization of shopping patterns implied some assumptions. For example, we theorized that combined trips, in comparison to separate trips, generally take longer to complete, but occur less frequently. While this is the rule rather than the exception, it need not always be true: especially when stores are located close to one-another, small "fill-in" combined trips may become feasible as well. Future work in this area would therefore benefit from a distinction between trip composition on one hand, and trip length and frequency on the other – along with their effects on monthly consumer spending.

Fifth, in our classification of shopping patterns, we adopted a discrete approach, e.g. consumers who visited multiple stores in a given month, were classified as either separate-trip shoppers, or combined-trip shoppers (in that month). In reality, consumers may fall somewhere between both ends of the scale. For example: they may alternate between separate- and combined-trips (possibly depending on their time available), and while some multiple-store shoppers may divide their purchases more or less equally across the stores they visit, others may more strongly distinguish between their primary and secondary store(s). Future studies could therefore benefit from a more continuous view on the dimensions of shopping patterns, as it allows for a richer perspective on how these dimensions shape consumer spending.

Finally, though our data allowed us to distinguish combined-trip from separate-trip shopping patterns, we could not assess the order in which the stores were visited on combined trips. Extant studies, however, suggest that this order may affect consumer spending, and how it is allocated across stores. Fox and Semple (2002), for example, state that consumers' purchasing behavior at a retailer becomes different when the retailer is not the first to be visited. Khan and Dhar (2006) find that "smart" purchases are more likely to drive subsequent "indulgent" purchases, which can amplify the "licensing" effects that may exist between a traditional store and a hard-discounter (in case the latter is visited first). It would, therefore, be interesting to study the spending implications of this shopping-pattern dimension as well.

Chapter 5 Conclusion

Today's grocery shopper is faced with the consequences of one of the most severe economic downturns in decades. Many consumers find themselves on a tighter budget than before, and are hard-pressed to better justify their purchases and/or cut back on their expenses. As a result, they increasingly behave as "smart shoppers", not being averse to expend additional effort in getting the most value for their money (Nielsen 2011).

Many current trends in grocery retailing can be traced back to this increased importance of smart shopping. One of them concerns the rise of the "hard-discounter" format. These basic, no-frills stores offer a limited assortment of very low-priced, high-quality private label products, providing consumers with an excellent opportunity to "trade down" and save money on their basket of groceries. Hard-discounters have become very popular over the years – in some cases accounting for up to 40% of grocery sales. Still, while many consumers shop at this format (up to 80% in some countries), most of them keep frequenting other stores as well (EFMI and CBL 2010).

Such "multiple-store" patronage, in itself, can actually be seen as another phenomenon indicative of smart shopping. Due to increases in both consumer mobility and the availability of different grocery stores (EFMI and CBL 2010), it has become easier for consumers to systematically visit more than one store. This, in turn, allows them to buy each product on their shopping list in the store that offers the best value – and thereby pick the best out of multiple "worlds". Multiple-store shopping behavior has become quite a common sight, with several academic and business sources reporting that the majority (60 to 80%) of consumers systematically allocate their purchases across more than one store (e.g. EFMI and CBL 2010; Gijsbrechts et al. 2008).

Despite the important role that hard-discounters and multiple-store shopping thus play in today's grocery business, both have received limited attention in the marketing literature (Cleeren et al. 2010; Gijsbrechts et al. 2008). This dissertation has therefore aimed to study both of these phenomena (and their interrelationship) in more depth – along with their implications for retailers and consumers alike. Our main findings are summarized in the next paragraph (§5.1), while the (managerial) recommendations and implications that emerge from these findings are presented in §5.2. Finally, §5.3 covers the main limitations of this dissertation, along with an overview of possible directions for future research.

5.1 Summary of Findings

The previous three research-based chapters all offered different perspectives on hard-discounters and/or multiple-store shopping. The second chapter focused on the implications of local hard-discounter entry for consumers' (multiple-store) shopping behavior and, as a result; the market performance of incumbent chains. The third chapter assessed whether economy private labels can help traditional retailers defend against the "hard-discounter threat". Finally, the fourth chapter examined to what extent new shopping opportunities, such as hard-discounter patronage and multiple-store shopping, actually help "smart shoppers" to reduce their grocery expenditures. For each of these three chapters, the main findings will be discussed below.

Chapter 2 – Close Encounter with the Hard-Discounter: A Multiple-Store Shopping Perspective on the Impact of Local Hard-Discounter Entry

While hard-discounters have become a force to reckon with in European grocery retailing and rapidly set foot in overseas markets as well, the format has not received much attention in the current marketing literature (which instead focused on an entirely different type of price fighter: the "large-discounter"). We address this gap by investigating how local hard-discounter entry affects the market performance of incumbent chains – as well as the underlying role that is played by inter-store complementarities, and the multiple-store shopping behavior they may give rise to.

We find that while incumbents suffer sizeable losses from local hard-discounter entry, they rarely see their best (single-store-loyal) customers switching away. Instead, stores primarily lose multiple-store-shopping customers, who already purchased only a fraction of their grocery purchases at the store prior to the hard-discounter's entry. This explains why losses to hard-discounters are generally more pronounced in terms of customer count than share-of-wallet. In addition, our findings suggest that losses to hard-discounters are less severe for incumbents that carry a complementary offer, and/or are conveniently located vis-à-vis the hard-discounter. Based on this notion, we tested the viability of a "cooperative" response strategy in which an incumbent enhances its complementarity with the hard-discounter, and find that it not only helps the incumbent to recover lost customers and spending – but also keeps the risk of a counter-attack by the hard-discounter low.

Chapter 3 – Battling for the Household's Category Buck: Can Economy Private Labels Help Defend Against the Hard-Discounter Threat?

"Traditional" retailers often employ a price-based strategy to defend against hard-discounters. One increasingly used approach is the introduction of an "economy private label" – a response that fits with the growing interest for "multi-tiered" private label programs. However, the current marketing literature does not give a clear indication on whether these economy private labels are actually successful in shielding against the hard-discounter threat. We therefore conduct a "difference-in-difference" analysis across 48 product categories, in which we compare retailers' losses to hard-discounters in the absence versus presence of an economy private label.

We find that both retailers' vulnerability to hard-discounters, as well as the effectiveness of economy private labels in reducing this vulnerability, varies widely across categories. In some categories, like coffee and vegetables, traditional retailers do not suffer much from hard-discounter entry. In other categories, however, sales losses are quite substantial; this particularly holds for categories that are (i) infrequently bought, (ii) relatively undifferentiated, and (iii) highly consistent in terms of product quality. We find that for this very same group of categories, economy private labels can be effectively used to reduce the losses from hard-discounter entry. Our results also suggest that as an economy private label becomes available in a larger number of categories, its performance as a defense mechanism vis-à-vis hard-discounters improves. Still, some categories remain in which traditional retailers are susceptible to hard-discounters, but where economy private labels do not help improve their situation – highlighting the need for an alternative defense mechanism.

Chapter 4 – Save or (Over-)Spend? How Shopping Pattern Choice Affects Consumer Grocery Spending

Consumers can nowadays engage in a variety of different shopping patterns. An often-cited reason to opt for a "non-standard" pattern, e.g. one that involves multiple (grocery) stores and/or the patronage of a hard-discounter, is the desire to save money. However, insights from the current (consumer behavior) literature suggest that different shopping patterns also affect consumers' ability and motivation to reap these savings – which raises the question whether, in the end, consumers actually spend less under these patterns. We shed more light on this issue by comparing consumers' expenditures across six different shopping patterns (defined along three dimensions), while controlling for household-specific and situational factors.

Our results show that, compared to a scenario in which a consumer buys all of his groceries at a single, "traditional" supermarket, consumers only spend less when this store would be fully replaced with a hard-discounter. Conversely, and inconsistent with the savings perspective, we find that all multiple-store shopping patterns lead to higher – rather than lower – expenditures. This suggests that multiple-store shoppers are not fully able and/or motivated to capitalize on the savings opportunities available to them – e.g. because of a larger number of prices and/or in-store stimuli to process. Expenditures turn out to be especially high when consumers embark on longer, “multi-store” trips (instead of visiting the stores on separate occasions). In these cases, spending is not even reduced when part of the household’s groceries is bought at a (low-priced) hard-discounter.

5.2 Implications and Recommendations

The findings of this dissertation lead to several practical insights and recommendations, for both retailers and consumers. These will be covered in this section.

The traditional retailer’s perspective

Impact of hard-discounters. For many traditional retailers, the rise of the hard-discounter format has become one of their greatest “sources of concern” (Cleeren et al. 2010) – leaving them desperately seeking for an appropriate response strategy that will keep these hard-discounters at bay (Nielsen 2007). However, our findings in chapter 2 and 3 put this issue into a new perspective. While traditional retailers should – naturally – expect to lose sales as a result of hard-discounter entry, chapter 2 first of all suggests that these losses are (on average) less severe than those reported for large-discounters like Wal-Mart (Ailawadi et al. 2010; Singh et al. 2006). In addition, after hard-discounter entry, traditional retailers still get to keep many of their loyal customers; that is, customers who buy (almost) their entire shopping basket at the store. Such customers are extremely valuable to retailers, as they account for a large part of their sales, and retaining them is easier than winning over new customers (Rosenberg and Czepiel 1984). Conversely, for customers who already frequented some of the retailer's competitors in a multiple-store shopping pattern, there is a higher risk that the retailer will be replaced by the new hard-discounter. Though chapter 4 shows that these multiple-store shoppers generally spend more money on groceries, only part was spent at the retailer in the first place – decreasing the importance of such losses in clientele.

Moreover, traditional retailers tend to feel the impact of hard-discounters only in part of their assortment. Chapter 2 shows that for numerous categories, consumers still prefer a traditional retailer to hard-discounters. As a result, as discussed in chapter 3, traditional retailers' sales losses to hard-discounters vary considerably across categories – even remaining completely absent in some of them.

Importance of location. As shown in chapter 2, the degree to which traditional retailers are susceptible to hard-discounters is influenced by their geographical location in a non-straightforward way. Not surprisingly, losses in patronage and share-of-wallet are lower when a hard-discounter entrant locates at a considerable distance, in which case it does not compete for the same consumers. More interesting, however, is the finding that hard-discounters entering in close proximity are also less harmful – the largest losses being recorded for instances where the hard-discounter opens shop at a moderate distance. For one, being located nearby the entrant increases the traditional retailer's chance of still being visited after the hard-discounter's entry. Given that (new) hard-discounter customers will rarely visit this format in isolation, a location close to the hard-discounter makes them more prone to keep the traditional retailer in their shopping pattern as well. In addition, being part of an attractive "one-stop shopping location" – in which consumers can easily combine visits to both the traditional and hard-discounter store – may actually bring in new traffic as well. While traditional retailers generally do not have a say in where their competitors locate (Foodmagazine 2009), hard-discounters often choose – on their own accord – to open up nearby. Thus, our results suggest that traditional retailers, in the face of such entry, should not take an overly defensive stance.

Importance of chain positioning. Chapter 2 shows that regardless of their location, some retailers are better able to keep their losses to hard-discounters in check than others. An important driver in this regard is the degree to which a traditional retailer complements the hard-discounter's offering. Because hard-discounters are usually visited alongside other stores, traditional retailers are more likely to be selected when they supplement the hard-discounter's offering with unique strengths of their own. Since hard-discounters' value-for-money proposition is hard to beat, those strengths will primarily lie in offering a wide range of products – particularly in categories where consumers' needs relate more to assortment than price. Hence, "upscale" supermarkets, with a clear focus on assortment selection rather than low prices, are more complementary to hard-discounters than supermarkets that seek a compromise between the two. Chapter 2 shows that the latter group – being "squeezed in the middle" (Foodmagazine 2009) – suffers more severe sales losses, and should thus be warier of hard-discounters.

Response strategies. This dissertation also provides insights into possible strategies that retailers may employ to (further) reduce their losses to hard-discounters. An important conclusion is that, rather than opting for an "across-the-board" strategy, traditional retailers should adjust their response on a category-by-category basis – as will be discussed below.

First of all, while chapters 2 and 3 show that traditional retailers have little to fear from hard-discounters in some categories (such as cereals and meat), these categories should definitely not be overlooked in formulating a response strategy – but can rather form a good starting point. Retailers are recommended to extend their current advantage over hard-discounters in these categories, by building on their unique strengths (e.g. through the expansion of their assortment, or the improvement of its composition). This makes them more complementary to the hard-discounter and, as discussed above, increases the likelihood that they will still be visited after the latter's entry.

Traditional retailers are considerably more vulnerable to hard-discounters in other categories, however. Chapter 3 reveals that this especially concerns categories that are (i) infrequently bought, (ii) relatively undifferentiated, and (iii) consistent in terms of product quality. Conveniently, these are the same categories in which traditional retailers can successfully prevent sales losses by carrying an economy private label. This corroborates the findings in chapter 2, which indicate that a price-based response is particularly effective in categories where traditional retailers are "weak". Traditional retailers are therefore recommended to employ an economy private label in such categories – and as such supplement the aforementioned "complementarity-enhancing" strategy (which focuses on "strong" categories instead). Additionally, while chapter 3 emphasizes that economy private labels will not work for every single category in which retailers are susceptible to hard-discounters, retailers should still introduce these products on a sufficiently broad scale – as we find that their effectiveness increases with the number of categories in which they are present.

Finally, chapter 4 points to a response strategy that not necessarily applies to a specific group of categories, but does tie in with the importance of multiple-store shopping in a hard-discounter context. We show that consumers who combine visits to a hard-discounter and a traditional retailer on the same shopping trip, may use their savings at the former as a "license to indulge" – and therefore spend more at the latter. We therefore suggest that traditional retailers (especially those who operate in close proximity of a hard-discounter, and thus attract many "combined-trip shoppers") strongly encourage such additional spending, e.g. by employing more in-store stimuli. This helps them to secure a larger part of the consumer's wallet – and thus compensate for the sales lost to the hard-discounter.

The hard-discounter's perspective

While none of the three core chapters of this dissertation have been written from the perspective of hard-discounters, our results do give rise to some implications and recommendations for this store format as well. Chapter 3 shows that hard-discounters primarily experience difficulty in securing a large share-of-sales among categories that are frequently purchased, strongly differentiated and/or where product quality is highly variable. Given these characteristics, if hard-discounters want to effectively compete with traditional retailers in this group of categories as well, they are advised to put more effort into reducing consumers' purchase risk (e.g. through quality assurance) – as well as to make their assortment more reflective of differences in consumer needs.

Even though hard-discounters perform much better sales-wise in categories with lower purchase frequency, product differentiation and/or quality variability, our findings also suggest that for these same categories, hard-discounters will experience fierce competition from the economy private labels that are deployed by their (traditional-format) competitors. This thus puts considerable pressure on hard-discounters' sales for these categories as well. Given that economy private labels are basic in nature and only of an "acceptable" quality, hard-discounters are again suggested to place more emphasis on the quality and/or sophistication of their products, in order to increase the added value of their assortment vis-à-vis economy private labels.

Chapter 2 provides several interesting insights as well. We find that hard-discounters are seldom visited in isolation, indicating that in order for a hard-discounter to be visited, it generally needs to be accompanied by other stores. This suggests that hard-discounters perform best when they make it convenient for consumers to visit them along their current store-of-choice, i.e. by locating in close proximity of (multiple) incumbents. Also, these incumbents should be as complementary to the hard-discounter as possible, as this increases the likelihood of (joint) patronage as well. This poses an interesting conflict: while hard-discounters generally are most complementary to “upscale” supermarkets, the latter – given their sophisticated private label programs – are also the most likely to carry an economy private label. While the current dissertation cannot provide a definitive recommendation on this matter, it may form an interesting venue for further research.

The consumer’s perspective

This dissertation also offers some interesting insights for grocery shoppers themselves. Chapter 2 signifies that, given consumers’ needs and preferences across different categories, no single store is likely to be the most satisfactory option for every category. Instead, consumers can better meet their needs by visiting more than one store, purchasing each category in the store whose offer best reflects their preferences. These advantages, or “complementarities”, are especially large when the stores strongly differ in focus and/or positioning – as is the case between (upscale) traditional supermarkets and hard-discounters. While the patronage of multiple stores also requires more effort, e.g. in terms of travel and/or shopping time, increases in consumer mobility and store clustering have made these additional “shopping costs” less severe – and thus less likely to weigh up against the benefits.

While multiple-store shopping thus allows consumers to simultaneously pursue different shopping objectives (that may vary by category), chapter 4 suggests that consumers who only (or predominantly) visit multiple stores out of a desire to save will generally be less successful. Our findings indicate that multiple-store shopping (which involves a much larger number of prices and in-store stimuli to process) actually leads shoppers to spend more than on single-store patterns – even when a hard-discounter is among the stores visited. These expenditures are particularly high when the consumer embarks on “combined trips”, i.e. visits multiple store destinations per shopping occasion.

In all, when consumers' main shopping goal is to cut back on their total grocery spending, they are advised not to engage in multiple-store shopping (and especially not in the form of combined-trips). However, when consumers, instead, seek to save money ("trade down") in some categories, so as to benefit from higher variety and/or quality ("trade up") in others, multiple-store shopping can be an effective way to reach these objectives – especially when both a traditional supermarket and a hard-discounter are visited.

5.3 Limitations and Future Research

Naturally, the research in this dissertation is subject to a number of limitations. While some were already mentioned in each of the three core chapters, others do not pertain to a single chapter. These limitations will be covered below, along with a discussion of the ensuing directions for future research in the area of hard-discounters and/or multiple-store shopping.

Response to hard-discounters. This dissertation puts a large focus on the evaluation of possible defense strategies for traditional retailers, in response to hard-discounters. The strategies covered largely pertain to adjustments in the retailer's (category) marketing mix, such as price cuts, assortment extensions, or the proliferation of (different types of) private labels. However, we did not yet explore the viability and/or effectiveness of strategies that are more communication-oriented. For example, should traditional supermarkets advertise themselves as "having everything hard-discounters have and more" – that is, offering both low prices and high-profile products (such as Albert Heijn did in 2010, with a campaign that emphasized its three price tiers)? Or should retailers rather differentiate themselves, and only advertise their unique selling points vis-à-vis hard-discounters (i.e. an extensive selection of national brands, or an excellent level of consumer service)?

On a related note, our finding that more complementary retailers are better able to withstand the hard-discounter threat begs the question on whether retailers should communicate these complementarities to consumers. While an explicit "association" with the hard-discounter may strongly stimulate store traffic (Foodmagazine 2009), it may simultaneously make the retailer's current customers more aware of (and interested in) its competitor. Future research should therefore take up this issue.

Moreover, it remains unclear how in-store marketing can be used by traditional retailers in their battle with hard-discounters. Given that consumers systematically visit both formats, should traditional retailers primarily use their in-store incentives to prevent consumers from buying "weak" categories at the hard-discounter? Or should they, instead, concentrate their efforts on more hedonic (higher-margin) categories, which consumers could then justify buying through their (projected) savings at the hard-discounter? This is another interesting topic for future studies to address.

Finally, future work in this area could investigate the (potential) role of word-of-mouth and/or social media. While recent marketing studies already corroborate the significance of these non-traditional forms of marketing communication (Stephen and Galak 2012; Villanueva, Yoo and Hanssens 2008), little is known on their effectiveness within the grocery retailing business. Marketing scholars could therefore investigate whether word-of-mouth and social media can help retailers in improving their position vis-à-vis hard-discounters – and if so, how they should be implemented.

Category differences. The findings of our dissertation point to considerable differences in how consumers behave across product categories. In chapter 2, we show that the importance that consumers attach to price and assortment varies over categories, and that this can lead to different store (format) preferences for different categories. However, our results did not document to what extent consumers actually act upon these preferences. In other words, it remains unclear: (i) how (multiple-store) shoppers allocate their purchases across different stores, (ii) whether this allocation is consistent with their needs across different categories, and (iii) which factors determine this degree of consistency. These questions form interesting starting points for future research. In addition, while chapter 2 provided examples of both categories in which consumers are primarily price-sensitive, and of categories in which they attach more value to assortment instead, less is known on what drives consumers to "trade up" or "trade down" in a category. Intrinsic category characteristics may play an important role here, which should be explored by future studies as well.

Chapter 3 further supports that consumers' store preferences vary between categories – as we find traditional retailers' losses to hard-discounters to be highly category-specific. Indeed, several industry sources confirm that hard-discounters' share-of-trade "is very different by category" (Nielsen 2007). In a similar vein, we find that the defensive ability of economy private labels vis-à-vis hard-discounters greatly differs across categories. While we conducted an exploratory analysis to determine in what types of categories economy private labels do and do not work, we were only able to make these inferences on a limited number of categories. As retailers come to carry economy private labels in many of their categories (Albert Heijn, for instance, nowadays offers more than 400 products under its "Euroshopper" label), marketing scholars can replicate and extend our analysis on a larger sample of categories.

While chapter 4 highlighted how much consumers spend on their entire grocery basket, across different shopping patterns, it did not drill down to the category level. This, also, is a fruitful venue for future research. Given our finding that multiple-store shoppers spend more on their groceries – despite the opportunities for savings that these patterns provide – it would be interesting to study in which categories consumers "overspend" (and, conversely, in which ones they actually do save money). Such knowledge would be of great value to retailers, for example in selecting in which categories to concentrate their (in-store) marketing efforts.

Data sources. Our primary source of data for the three core chapters comprises purchase data of GfK's Dutch consumer panel, which consists of about 6000 households in total. This had several implications for our analyses, delineated below.

First, chapters 2 and 3 investigate how traditional chains' customer count, share-of-wallet and (volume) sales are affected by the advent of the hard-discounter format, and how they should best respond. Naturally, we do so by analyzing the purchase behavior of individual households. However, these panel members can be quite sparsely located across some of the markets in which the retailers operate. To add further confidence to our findings, it may therefore be beneficial to augment our current analyses with actual (outlet) sales data – if available.

Second, while the panel purchase data allow us to track in detail how households respond to different marketing stimuli, they do not provide insights into the underlying motivations for such behavior – forcing us to make assumptions on these matters. For example, an important question is: why do consumers, in some instances, prefer hard-discounter products over those offered at traditional retailers (particularly when some of these, e.g. economy private labels, are low-priced as well)? Furthermore: what is (are) consumers' main shopping goal(s) behind different shopping patterns, and how do those goals shape their purchase and/or spending behavior within the patterns? These are interesting questions for future research to address – for example by making use of survey data.

Third, even though our data allowed us to characterize consumers' shopping trips based on the number of stores visited (which was used in both chapters 2 and 4), other classifications were much less evident – or even impossible – to make. For example, we did not make a formal distinction between "major" and "fill-in" shopping trips (e.g. Kahn and

Schmittlein 1989), nor could we account for whether a shopping list was used to guide the trip. Since chapter 4 showed that the way in which consumers shop can have a strong effect on their subsequent decisions, future studies should investigate how these trip characteristics may shape consumer behavior, e.g. the amount spent or the (types of) products purchased.

Market setting. Another limitation is that our data pertain only to the Netherlands. First, the Dutch grocery market is characterized by a high “outlet density” (EFMI and CBL 2010), which allows consumers to engage in multiple-store shopping – and to switch between stores on a category-by-category basis – with relative ease. As shown in this dissertation, such behavior strongly shapes retailers’ sales. While the same phenomena are likely to apply to other markets as well (e.g. in the US, while stores are less clustered, consumers are more mobile), a replication in other countries would shed further light on the generalizability of our results.

Furthermore, even though the Dutch market is highly competitive, and relatively sophisticated in nature, it lacks the presence of two retailing formats that are important elsewhere: the “large-discounter” (e.g. Wal-Mart) and the “hypermarket” (e.g. Carrefour). In addition, the online grocery channel is still in its infancy – only market leader Albert Heijn has a large-scale online division, and the share of Dutch consumers who shop online for groceries on a structural basis (i.c. each month) amounts to less than 2% (EFMI and CBL 2010). This is in stark contrast with the UK, for example, where the three top retailers all operate a full-fledged online channel next to their “brick-and-mortar” stores (Twinkle Magazine 2012). All of these formats and/or channels likely compete with hard-discounters in different ways, and give rise to a greater range of shopping patterns consumers can engage in. Again, this encourages researchers to incorporate other countries in their studies as well, in order to gain a broader insight into the possible implications of hard-discounters and (multiple-store) shopping patterns.

Current and future developments. It should be emphasized that this dissertation, and the data that were used for its development, provide a “snapshot” of the current state of grocery retailing. However, the “wheel of retailing” is constantly in motion, with retailers continuously making adjustments to their positioning, communication strategies and/or marketing mix. For instance, while hard-discounters initially entered the market as “no-nonsense” price-fighters, they nowadays also target more affluent (and quality-conscious) consumers, for example by stocking national brands and/or adding specialized sections (e.g. for fresh produce or bakery) to their stores (Foodmagazine 2012; Ter Braak 2012). This makes them increasingly similar in positioning to the traditional retailers with which they compete. To illustrate, some business executives even already classify Lidl as a “service supermarket” (Foodmagazine 2012).

Another example lies in the private label programs that are employed by retailers. While chapter 3 shows that economy private labels do not help traditional retailers defend against hard-discounters in every category, it also indicates that they tend to become more effective as their rollout proceeds. Given that many retailers nowadays have introduced their economy private label in the main majority of categories, it may be interesting to re-evaluate the defensive ability of these products. In addition, retailers have added new types of private labels to their assortments as well. Traditional retailers, like the UK-based Tesco, have started to sell “discount brands” – private labels that match hard-discounter products in terms of both price and quality. Meanwhile, the hard-discounters themselves have introduced “premium” private labels into their assortment, such as Aldi with its “Prestige” brand (FoodPersonality 2012). Again, this development increases the similarities between both formats even further.

Not only the retailers themselves are changing, though – their customers evolve as well. For example, not only has the number of consumers that are receptive of hard-discounters grown (Steenkamp and Kumar 2009), these same consumers – gaining trust in the hard-discounter's offer over the years – may also have become more willing to assign a greater role to hard-discounters in their shopping patterns (buying an increasingly large part of their basket at the format). This would explain why hard-discounters' initially grow at a slow pace, but then gain considerable momentum over the years (Silverstein and Roche 2006). Future studies may further investigate this topic, and thereby gain more insight into what categories consumers use to "sample" the hard-discounter, and whether consumers' quality impressions can "spill over" to other categories as well.

Finally, the market environment in which retailers and their customers meet is also unlikely to remain in its present-day state. Several business resources report that the current economic downturn – and its detrimental effect on consumers and businesses alike – is slowly fading away (Distrifood 2012; EFMI and CBL 2010). This raises the question of whether the trends of hard-discounter patronage and multiple-store shopping will continue to hold in the near future. On one hand, consumers may again become more lenient in setting their grocery budgets – reducing the need for "smart shopping". On the other hand, as Lamey et al. (2007) show in the context of private labels, consumers may also choose to persist in such price-conscious behavior – even when the "bad economic times are long over". These are interesting issues for future research to address.

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Appendices

Appendix 1 Shopping Pattern Choice and Spending Share Model

In each month, households' shopping decisions involve four interrelated choices, which we model in a nested fashion.

Single- versus multiple-store shopping

Each month, households are assumed to make a decision on whether to purchase their groceries exclusively within a single chain, or to visit multiple chains. Assuming that households are utility-maximizers, this choice can be expressed by a binary logit model:

[A.1] $P_t^h(MSS) = \dfrac{e^{W_t^h(MSS)}}{e^{W_t^h(SSS)} + e^{W_t^h(MSS)}}$, with:

$$W'^h_t(MSS) = W_t^h(MSS) + \upsilon^h_{Mt} = \lambda_0 + \lambda_1 * Month_t + \zeta * IV_t^h(MSS) + \upsilon^h_{Mt}$$
$$W'^h_t(SSS) = W_t^h(SSS) + \upsilon^h_{St} = \zeta * IV_t^h(SSS) + \upsilon^h_{St}$$

$P_t^h(MSS)$ is the probability that household *h* visits multiple stores in month *t*. W_t^h represents systematic utility, while υ^h_{Mt} and υ^h_{St} are Gumbel-distributed errors. $Month_t$ is a trend variable controlling for evolutions in multiple-store shopping behavior independent of local market characteristics. $IV_t^h(MSS)$ and $IV_t^h(SSS)$ are inclusive values (to be specified below), reflecting the expected maximum utility from the multiple- and single-store shopping patterns, respectively, in which household *h* can engage in month *t*.

Shopping Organization: Separate-trip versus combined-trip shopping

Households that patronize multiple stores must decide whether to organize their trips to these stores in separate-trip or combined-trip patterns. Again, we adopt a binary logit model:

[A.2] $P_t^h(CMB \mid MSS) = \dfrac{e^{V_t^h(CMB)/\zeta}}{e^{V_t^h(SEP)/\zeta} + e^{V_t^h(CMB)/\zeta}}$, with:

$$V'^h_t(CMB) = V_t^h(CMB) + \omega_{Ct}^h = \gamma_0 + \gamma_1 * Month_t + \xi * IV_t^h(CMB) + \omega_{Ct}^h$$
$$V'^h_t(SEP) = V_t^h(SEP) + \omega_{St}^h = \xi * IV_t^h(SEP) + \omega_{St}^h$$

$P_t^h(CMB \mid MSS)$ is the conditional probability that household *h*, given that it visits multiple stores, visits them on combined trips; V_t^h is a systematic utility component and ω_{Ct}^h and ω_{St}^h are Gumbel-distributed errors. $Month_t$, again, controls for any exogenous trends in combined-trip shopping behavior, and $IV_t^h(CMB)$ and $IV_t^h(SEP)$ are inclusive values (to be further specified), reflecting the expected maximum utility from combined- and separate-trip patterns, respectively. The denominator of [A.2] is used to specify the inclusive value of MSS in [A.1]: $IV_t^h(MSS) = \ln(e^{V_t^h(SEP)/\zeta} + e^{V_t^h(CMB)/\zeta}) = \ln(e^{\xi * IV_t^h(SEP)/\zeta} + e^{[\gamma_0 + \gamma_1 * Month_t + \xi * IV_t^h(CMB)]/\zeta})$.

Store (set) Choice

A household's decision on which store or set of stores to select is captured by a multinomial logit model. For each individual store, the probability that this store is selected from all the stores that are available to the household, is specified as follows:

[A.3a] $P_t^h(r \mid SSS) = \dfrac{e^{U_t^h(r)/\zeta}}{\sum_{k=1}^{K_t^h} e^{U_t^h(k)/\zeta}}$, with:

$$U'^h_t(r) = U_t^h(r) + \eta_t^h(r) = instU^h(r) + bsktU_t^h(r) + trvlU^h(r) + \eta_t^h(r)$$

$P_t^h(r \mid SSS)$ is the conditional probability that household *h* patronizes store *r* in month *t*, given that it visits only one store that month, while $U_t^h(r)$ and $\eta_t^h(r)$ are again the systematic and (Gumbel-distributed) random utility components. Store selection is a function of three types of utility: (i) in-store utility ($instU^h(r)$): benefits obtained from the physical environment or customer service in the store, (ii) basket utility ($bsktU_t^h(r)$): benefits and costs of purchasing one's basket (shopping list) of groceries at the store, and (iii) travel (dis)utility ($trvlU^h(r)$): transportation costs involved in visiting the store (for the drivers of these utility components: see Tables 2.1 and 2.3 in the main text). The number of stores included in the denominator of [A.3a], K_t^h, reflects a household's consideration set. The log of the denominator of [A.3a] again serves as an inclusive value in equation [A.1]: $IV_t^h(SSS) = \ln(\sum_{k=1}^{K_t^h} e^{U_t^h(k)/\zeta})$.

Store set selection. Households can also choose to visit a set of stores. Consistent with Gijsbrechts et al. (2008), we restrict the maximum number of stores within a set to two. As such, a household's choice between all available store sets (given that the household engages in a combined-trip pattern) can be expressed as:

[A.3a] $$P_t^h(r,s \mid CMB) = \frac{e^{U_t^h(r,s|CMB)/\xi}}{\sum_{k=1}^{K_t^h-1} \sum_{l=k+1}^{K_t^h} e^{U_t^h(k,l|CMB)/\xi}}$$

$P_t^h(r,s \mid CMB)$ is the conditional probability that household *h*, in month *t*, engages in a shopping pattern that comprises stores *r* and *s*, visited on combined trips. The total utility of this option is given by $U'^h_t(r,s \mid CMB) = U_t^h(r,s \mid CMB) + \varepsilon_t^h(r,s \mid CMB)$, where $U_t^h(r,s \mid CMB)$ is the systematic part of utility (composed of the in-store, basket and travel utilities associated with combined trips to stores *r* and *s*), and $\varepsilon_t^h(r,s \mid CMB)$ is a Gumbel-distributed error component, with location parameter zero and scale parameter 1/ξ. We further know that the metric $\varepsilon *_t^h(r,s \mid CMB) = \max_{\substack{(k,l),\\(k,l)\neq(r,s)}} \{U_t^h(k,l \mid CMB) + \varepsilon_t^h(k,l \mid CMB)\}$ is Gumbel-distributed with location parameter $\xi * \ln(= \sum_{\substack{(k,l),\\(k,l)\neq(r,s)}} \exp(U_t^h(k,l \mid CMB)/\xi))$ (Ben-Akiva and Lerman 1985). The difference between this metric and the original error, $\Delta\varepsilon_t^h(r,s \mid CMB) = \varepsilon *_t^h(r,s \mid CMB) - \varepsilon_t^h(r,s \mid CMB)$, both of which are Gumbel-distributed, then follows a logistic distribution, with corresponding cumulative density function (Zhang and Krishnamurthi 2004):

$$[A.3b]\ F(\Delta\varepsilon_t^h(r,s\,|\,CMB)) = \frac{1}{1+\exp(\frac{1}{\xi}(\xi * \ln(\sum_{\substack{(k,l),\\(k,l)\neq(r,s)}} \exp(U_t^h(k,l\,|\,CMB)/\xi)) - \Delta\varepsilon_t^h(r,s\,|\,CMB)))}$$

For the choice of a set of stores, visited on separate trips, the same expressions apply (except that *CMB* is now replaced by *SEP* in the above equations).

Spending share

The derivations for the spending share model, and its correlation with the store-set choice component, closely follow those developed by Zhang and Krishnamurthi (2004). Given that household *h*, in month *t*, engages in a combined-trip pattern involving stores *r* and *s*, we model the spending share allocated to store *r* as a binary logistic function:

$$[A.4]\quad m_t^h(r\,|\,(r,s),CMB) = \frac{e^{S_t^h(r|(r,s),CMB)+\vartheta_t^h(r|(r,s),CMB)}}{1+e^{S_t^h(r|(r,s),CMB)+\vartheta_t^h(r|(r,s),CMB)}}$$, or equivalently,

$$\ln(\frac{m_t^h(r\,|\,(r,s),CMB)}{1-m_t^h(r\,|\,(r,s),CMB)} = S_t^h(r\,|\,(r,s),CMB) + \vartheta_t^h(r\,|\,(r,s),CMB)$$, where:

$$\begin{aligned} S_t^h(r\,|\,(r,s),CMB) = {} & \phi_1 * (instU^h(r) - instU^h(s)) \\ & + \phi_2 * (bsktU_t^h(r) - bsktU_t^h(s)) * (1 + Comp_t^h(r,s))^{\phi_3} \end{aligned}$$

and where $\vartheta_t^h(r\,|\,(r,s),CMB)$ follows a logistic distribution with location parameter zero and scale parameter δ_ϑ, or: $F(\vartheta_t^h(r\,|\,(r,s),CMB)) = \frac{1}{1+\exp(-\vartheta_t^h(r\,|\,(r,s),CMB) * \delta_\vartheta)}$.

Similar to Zhang and Krishnamurthi (2004), we now introduce the correlation between the bivariate distributions in [A.3b] and [A.4] through a flexible bivariate logistic function:

$$[A.5]\quad \begin{aligned} F(\Delta\varepsilon_t^h(r,s\,|\,CMB), \vartheta_t^h(r\,|\,(r,s),CMB)) = {} & F(\Delta\varepsilon_t^h(r,s\,|\,CMB)) * F(\vartheta_t^h(r\,|\,(r,s),CMB)) \\ & * (1 + \chi * (1 - F(\Delta\varepsilon_t^h(r,s\,|\,CMB))) \\ & * (1 - F(\vartheta_t^h(r\,|\,(r,s),CMB)))) \end{aligned},$$

where χ is a parameter between -1 and 1. Then, as shown by Zhang and Krishnamurthi

(2004), the probability that store set (*r*,*s*) is selected and that a portion $m_t^h(r\,|\,(r,s),CMB)$ of the household's monthly budget is spent in store *r*, given a combined shopping pattern, is given by:

[A.6]
$$P_t^h((r,s)\,|\,CMB; m_t^h(r\,|\,(r,s),CMB)) = \frac{e^{U_t^h(r,s|CMB)/\xi}}{\sum_{k=1}^{K_t^h-1}\sum_{l=k+1}^{K_t^h} e^{U_t^h(k,l|CMB)/\xi}} * \frac{\delta_g e^{-@_t^h(r|r,s)*\delta_g}}{(1+e^{-@_t^h(r|r,s)*\delta_g})^2}$$
$$*(1+\chi*(1-\frac{e^{U_t^h(r,s|CMB)/\xi}}{\sum_{k=1}^{K_t^h-1}\sum_{l=k+1}^{K_t^h} e^{U_t^h(k,l|CMB)/\xi}})*\frac{-1+e^{-@_t^h(r|r,s)*\delta_g}}{1+e^{-@_t^h(r|r,s)*\delta_g}}))$$
, where:

$$@_t^h(r\,|\,r,s) = \ln(\frac{m_t^h(r\,|\,(r,s),CMB)}{1-m_t^h(r\,|\,(r,s),CMB)}) - \phi_1*(instU^h(r)-instU^h(s))$$
$$+\phi_2*(bsktU_t^h(r)-bsktU_t^h(s))*(1+Comp_t^h(r,s))^{\phi_3}$$

Similar derivations lead to an equivalent expression (but with *SEP* replacing *CMB*, and parameters φ_1, φ_2 and φ_3 replacing ϕ_1, ϕ_2 and ϕ_3) for the simultaneous probability of choosing set (*r*,*s*) and spending a share $m_t^h(r\,|\,(r,s),SEP)$ at store *r*, given a separate-trip pattern.

Estimation

To estimate the model, using a latent class approach to capture random household heterogeneity, we maximize the following log-likelihood function:

[A.7]
$$\sum_h \ln \sum_g \pi^g \prod_t \begin{array}{l} (1-P_t^{h,g}(MSS))^{1-y_t^h(MSS)} * (P_t^{h,g}(MSS))^{y_t^h(MSS)} * \\ (1-P_t^{h,g}(CMB\,|\,MSS))^{1-y_t^h(CMB)} * (P_t^{h,g}(CMB\,|\,MSS))^{y_t^h(CMB)} * \\ (\prod_{k=1}^{K_t^h} P_t^{h,g}(k\,|\,SSS)^{y_t^h(k|SSS)*(1-y_t^h(MSS))}) * \\ (\prod_{k=1}^{K_t^h-1}\prod_{l=k+1}^{K_t^h} P_t^{h,g}((k,l)\,|\,SEP; m_t^{h,g}(k\,|\,(k,l),SEP))^{y_t^h(k,l|SEP)*(1-y_t^h(CMB))*y_t^h(MSS)}) * \\ (\prod_{k=1}^{K_t^h-1}\prod_{l=k+1}^{K_t^h} P_t^{h,g}((k,l)\,|\,CMB; m_t^{h,g}(k\,|\,(k,l),CMB))^{y_t^h(k,l|CMB)*y_t^h(CMB)*y_t^h(MSS)})) \end{array}$$

Here, π^g is the size of household-segment *g*, and the *y*'s are indicator variables reflecting the household's actual choice. Like Zhang and Krishnamurthi (2004), we set the scale parameter δ_g equal to 1 for stability.

Appendix 2 Estimation of Category-Specific Price and Assortment Sensitivities

Both our shopping list attraction and inter-store complementarity measures are based on the stores' category-by-category attractiveness ($Attr_t(c,r)$). These attractions are, in turn, specified as a function of the stores' category price, assortment size and PL share in the category. Estimating the effects of these variables simultaneously with the shopping pattern choice parameters would make the model exceedingly complex. Hence, to obtain the parameters associated with these variables, we adopt a two-step approach similar to Bell and Lattin (1998). First, we use category-, chain- and household-specific data to obtain an overall indication of price, assortment and private label responsiveness by product category, across households and chains. Based on these category-specific parameters, we then calculate the list attractions and complementarities for each store (pair). Though we use the same sample to estimate the category responsiveness parameters on the one hand, and the parameters of the shopping pattern choice- and spending model on the other, there is no concern about endogeneity. The reason is that (i) the parameters $\delta_{A,c}$, $\delta_{P,c}$ and $\delta_{PL,c}$ capture category responsiveness to assortment size, price and private label presence in general – such that household, chain and shopping pattern effects are averaged out, and (ii) these parameters serve to calculate basket attractions and store complementarities across all categories, which are inputs to a model with (chain- and) consumer-specific parameters (see Bell and Lattin 1998; Campo, Gijsbrechts and Nisol 2003 and Fox et al. 2004 for similar arguments).

The model used to assess the category-responsiveness parameters of interest, $\delta_{A,c}$, $\delta_{P,c}$ and $\delta_{PL,c}$, takes the following form:

[A.8] $VolShare_t^h(c,r) = \dfrac{e^{Z_t^h(c,r)}}{\sum_{k=1}^{K_t^h} e^{Z_t^h(c,k)}}$, with:

$$Z'^h_t(c,r) = Z_t^h(c,r) + \kappa_t^h$$
$$= \delta_{A,c} * Assort_t(c,r) + \delta_{P,c} * Price_t(c,r) + \delta_{PL,c} * PLshare_t(c,r)$$
$$+ \delta_{S,c} * Size^h(r) + \delta_{D,c} * Dist^h(r) + \kappa_t^h$$

We operationalize $VolShare_t^h(c,r)$ as the share of household *h*'s total purchase volume in category *c* within month *t*, that is bought in store *r*. Z_t^h and κ_t^h are the systematic and random components of utility, respectively. To make the effects of assortment size, price and PL share comparable within categories, we standardize $Assort_t(c,r)$, $Price_t(c,r)$ and $PLshare_t(c,r)$ across chains and time. Finally, we include stores' selling surface and distance from the household as control variables.

The estimation results are summarized in Table A.1. The majority of the estimated coefficients is significant and has the expected sign. Using these estimates, we compute predicted differences in category attractiveness between HDs and traditional stores. The average differences are reported in Table A.2. The results are in line with expectations on the type of categories where HDs are typically strong (i.e. provide an important value advantage) or weak (quality advantage of traditional stores).

TABLE A.1
Summary of Assortment, Price and Store Brand Effects on Category Attractions

	Assortment size coefficient ($\delta_{A,c}$)	**Price level coefficient ($\delta_{P,c}$)**	**% Store brands coefficient ($\delta_{PL,c}$)**
Number of positive (significant positive) effects	42 (37)	6 (5)	11 (10)
Number of negative (significant negative) effects	10 (8)	46 (41)	41 (39)
Mean coefficient across categories	.161	-.263	-.610
Range of coefficients across categories	(-.230, .766)	(-1.137, .137)	(-2.909, .863)

TABLE A.2
Differences in Category Attractions Between Traditional Chains (TC) and Hard-Discounters (HD)

Product category	Attraction difference [TC – HD][a]	Sign test[b]	Product category	Attraction difference [TC – HD]	Sign test
Strong in traditional chains			*Weak in traditional chains*		
Baking products	.959	14	Chocolate products	-.485	14
Sauces	.822	14	Cheese	-.478	12
Cleaning products	.753	13	Specialty bread	-.451	14
Meat[c]	.666	14	Eggs	-.410	14
Diet products	.615	14	Sugar	-.397	14
Perfumes	.575	14	Fish	-.352	12
Vinegars	.550	14	Paper towels	-.282	13
Ketchups & mayonaise	.549	14	Sandwich fillings	-.266	10
All-purpose cleaners	.531	14	Cosmetics: skin	-.261	14
Hot drinks	.474	12	Dishwashing products	-.250	11
Air fresheners	.423	8	Pickles	-.211	10
Pet food	.402	14	Milk substitutes	-.189	9
Potatoes	.379	14	Soft drinks	-.183	14
Cosmetics: hair	.370	11	Milk & yoghurt drinks	-.178	14
Spices	.360	12	Salads	-.162	13
Rice & pasta	.356	14	Salty snacks	-.134	10
Breakfast cereals	.325	11	Diapers	-.126	8
Dental care	.286	9	Laundry detergents	-.123	8
Meals	.275	12	Cold cuts	-.105	10
Beers	.199	14	Biscuits	-.082	10
Soup	.193	14	Dairy products	-.039	7
Bread	.188	14	Alcoholic drinks (non-beer)	-.037	6
Vegetables	.140	14	Sweets	-.025	8
Fruit	.115	13	Bakery products	-.012	4
Butter	.071	6	Pastry	-.007	9
Ice cream	.006	4			
Bread substitutes	.002	5			

[a] Attraction differences are computed as the category's mean attraction across traditional chains and time, minus the category's mean attraction across hard-discounters and time.
[b] Number of hard-discounter/traditional supermarket-pairs (out of 14) for which a sign test supports the hypothesized direction of the difference in the chains' attractions (α=.05). For example, for hot drinks, a sign test supports that the traditional supermarket has higher attraction in the category (than the hard-discounter) for 12 out of 14 possible hard-discounter/traditional supermarket-pairs.

Appendix 3 Marginal Effects and Elasticities

Notation

The parameters are the same as in the main text: ζ is the inclusive value parameter at model layer A (single- versus multiple-store shopping), ξ is the inclusive value parameter at model layer B (separate versus combined shopping), β_3 and β_4 are the list-attraction and distance parameter, respectively, and θ and ψ are the complementarity parameters for separate and combined trips. Moreover, a "|" in the probability points to conditionality, and a "," to simultaneity. For instance, $P_t^h(r,s,CMB,MSS)$ would be the probability that store set *r* and *s* is selected in a multiple-store combined shopping pattern. This probability equals:

$P_t^h(r,s,CMB,MSS) = P_t^h(r,s \mid CMB)P_t^h(CMB \mid MSS)P_t^h(MSS) = P_t^h(r,s,CMB)P_t^h(MSS)$.

Or, as another example, $P_t^h(r \mid CMB)$ is the probability that the consumer visits store *r* (that is, selects a store set involving *r*), given that he engages in combined shopping. This would be the sum of probabilities $P_t^h(r,l \mid CMB)$ across all stores *l* other than *r*.

Impact of marginal utility changes

As a starting point, we derive expressions for the change in patronage probability of a store *r*, resulting from a marginal change in the systematic utility components, that is: (i) the utility of store *r* in a SSS pattern ($U_t^h(r)$), (ii) the utility of store *r* in a combined-trip MSS pattern together with store *s* ($U_t^h(r,s \mid CMB)$), and (iii) the utility of store *r* in a separate-trip MSS pattern together with store *s* ($U_t^h(r,s \mid SEP)$). After some tedious derivations (details can be obtained from the authors), the following expressions for the marginal effects are obtained.

Impact of marginal increase in $U_t^h(r)$ *on* $P_t^h(r)$*:*

[A.9a] $$\frac{\partial P_t^h(r)}{\partial U_t^h(r)} = P_t^h(r,SSS)\left[\frac{1}{\zeta} + \left(1 - \frac{1}{\zeta}\right)P_t^h(r \mid SSS) - P_t^h(r,SSS)\right] - P_t^h(r,SSS)P_t^h(r,MSS)$$

The first term on the right hand side gives the patronage change in single-store shopping, where the expression in squared brackets would typically be positive. The second term gives the change in patronage of *r* in multiple-store shopping patterns, this effect is clearly negative. The total impact on the patronage probability of store *r* can be simply re-written as:

$$\text{[A.9b]} \quad \frac{\partial P_t^h(r)}{\partial U_t^h(r)} = P_t^h(r, SSS)\left[\frac{1}{\zeta} + \left(1 - \frac{1}{\zeta}\right)P_t^h(r \mid SSS) - P_t^h(r)\right]$$

Impact of marginal increase in $U_t^h(r, s \mid CMB)$ *on* $P_t^h(r)$:

This effect comprises four components. The first component is the change (=increase) in the choice probability of *r* in a combined pattern together with *s*:

$$\text{[A.10a]} \quad P_t^h(r, s, CMB, MSS)\left[\begin{array}{r}\frac{1}{\xi}\left(1 - P_t^h(r, s \mid CMB)\right) + \frac{1}{\zeta}P_t^h(r, s \mid CMB)\left(1 - P_t^h(CMB \mid MSS)\right) \\ + \left(1 - P_t^h(MSS)\right)P_t^h(CMB \mid MSS)P_t^h(r, s \mid CMB)\end{array}\right]$$

The second component is the change in single-store patronage for *r*:

$$\text{[A.10b]} \quad -P_t^h(r \mid SSS)P_t^h(SSS)P_t^h(r, s, CMB, MSS)$$

Third, we have the change in separate-store patronage for *r* in a set with any other store *l*:

$$\text{[A.10c]} \quad P_t^h(r, s, CMB, MSS)P_t^h(r, SEP \mid MSS)\left[1 - \frac{1}{\zeta} - P_t^h(MSS)\right]$$

The fourth component is the change in patronage in combined-store shopping for *r* in a set with any store different from *s*:

$$\text{[A.10d]} \quad \begin{array}{l} P_t^h(r, s, CMB, MSS)\left(P_t^h(r \mid CMB) - P_t^h(r, s \mid CMB)\right) \\ * \left[-\frac{1}{\xi} + \frac{1}{\zeta}(1 - P_t^h(CMB \mid MSS)) + (1 - P_t^h(MSS))P_t^h(CMB \mid MSS)\right]\end{array}$$

While the first component is expected to be positive, the other components are typically negative. Summing up these four components and rearranging terms, the total effect can be re-written as:

[A.10e] $$\frac{\partial P_t^h(r)}{\partial U_t^h(r,s\,|\,CMB)} = P_t^h(r,s,CMB,MSS)\begin{bmatrix} \frac{1}{\xi} + \left(\frac{1}{\zeta} - \frac{1}{\xi}\right) P_t^h(r\,|\,CMB) \\ + \left(1 - \frac{1}{\zeta}\right) P_t^h(r\,|\,MSS) - P_t^h(r) \end{bmatrix}$$

Impact of marginal increase in $U_t^h(r,s\,|\,SEP)$ *on* $P_t^h(r)$ *:*

This effect, again, comprises four components, similar to the ones above. The change in single-store patronage for *r* is now given by:

[A.11a] $-P_t^h(r\,|\,SSS)P_t^h(SSS)P_t^h(r,s,SEP,MSS)$

Similar to before, the total effect can be written as:

[A.11b] $$\frac{\partial P_t^h(r)}{\partial U_t^h(r,s\,|\,SEP)} = P_t^h(r,s,SEP,MSS)\begin{bmatrix} \frac{1}{\xi} + \left(\frac{1}{\zeta} - \frac{1}{\xi}\right) P_t^h(r\,|\,SEP) \\ + \left(1 - \frac{1}{\zeta}\right) P_t^h(r\,|\,MSS) - P_t^h(r) \end{bmatrix}$$

Expressions [A.9b], [A.10e] and [A.11b] show that the impact of a utility change depends on (i) the probability of patronage of store *r*, conditional on a specific organization of the MSS shopping pattern ($P_t^h(r\,|\,SEP)$ and $P_t^h(r\,|\,CMB)$); (ii) the probability of patronage of store *r*, conditional only on whether the consumer selects a single- or a multiple-store shopping pattern ($P_t^h(r\,|\,SSS)$ and $P_t^h(r\,|\,MSS)$); and (iii) the unconditional patronage probability of store *r* ($P_t^h(r)$). In Table 2.7 of the main text, elasticities are calculated for the average level of these probabilities for the considered incumbent, across the entire data set.

Marginal Effect of Specific Explanatory Variables

For illustrative purposes, we derive the marginal effects for three variables: the distance between two stores *r* and *s*, the complementarity of stores *r* and *s*, and the list attraction of store *r*. Below, we derive the ceteris-paribus impact of a marginal change in these variables, on the patronage probability of store *r*. We then comment on how changes in specific marketing-mix instruments within a category, can be calculated through.

Impact of a change in distance between stores r and s on patronage of r (ceteris paribus). The distance between stores *r* and *s* only intervenes in the utility of the store set (*r*,*s*) in a combined pattern. Hence, the distance impact on the total patronage probability for store *r* can be obtained by multiplying [A.10e] with the marginal impact of distance on this utility:

$$\frac{\partial P_t^h(r)}{\partial U_t^h(r,s\,|\,CMB)}\frac{\partial U_t^h(r,s\,|\,CMB)}{\partial Dist^h(r,s\,|\,CMB)} = P_t^h(r,s,CMB,MSS)\begin{bmatrix}\dfrac{1}{\xi}+\left(\dfrac{1}{\zeta}-\dfrac{1}{\xi}\right)P_t^h(r\,|\,CMB) \\ +\left(1-\dfrac{1}{\zeta}\right)P_t^h(r\,|\,MSS)-P_t^h(r)\end{bmatrix}$$

$$*\frac{\beta_4}{(Dist^h(r,s\,|\,CMB)+1)}$$

Using expression [A.10a] above, we further observe that the probability of a combined shopping pattern involving store *r* and *s* will change by:

$$\frac{\partial P_t^h(r,s,CMB,MSS)}{\partial U_t^h(r,s\,|\,CMB)}\frac{\partial U_t^h(r,s\,|\,CMB)}{\partial Dist^h(r,s\,|\,CMB)} = P_t^h(r,s,CMB,MSS)*$$

$$\begin{bmatrix}\dfrac{1}{\xi}\left(1-P_t^h(r,s\,|\,CMB)\right)+\dfrac{1}{\zeta}P_t^h(r,s\,|\,CMB)\left(1-P_t^h(CMB\,|\,MSS)\right) \\ +\left(1-P_t^h(MSS)\right)P_t^h(CMB\,|\,MSS)P_t^h(r,s\,|\,CMB)\end{bmatrix}*\frac{\beta_4}{(Dist^h(r,s\,|\,CMB)+1)}$$

– a change that is clearly negative for negative values of the distance parameter.

These expressions reveal that for a given household, any decrease in the distance between stores *r* and *s* (that will not affect the distance between the consumer's home and each of the stores, ceteris paribus) will (i) enhance the probability of combined shopping for that store pair but, at the same time, reduce store *r*'s single-store shopping propensity (and its propensity to be chosen on separate trips, or combined trips along with other stores).

Impact of a change in complementarity between stores r and s (*ceteris paribus*). This complementarity intervenes both in the separate and combined utility components of store set (*r*,*s*). Hence, we now have to sum up the effect through both of these routes, or:

$$\frac{\partial P_t^h(r)}{\partial Comp_t^h(r,s)} = \frac{\partial P_t^h(r)}{\partial U_t^h(r,s\,|\,SEP)}\frac{\partial U_t^h(r,s\,|\,SEP)}{\partial Comp_t^h(r,s)} + \frac{\partial P_t^h(r)}{\partial U_t^h(r,s\,|\,CMB)}\frac{\partial U_t^h(r,s\,|\,CMB)}{\partial Comp_t^h(r,s)}$$

Using the expressions derived earlier, this is easily found to be equal to:

$$\frac{\partial P_t^h(r)}{\partial Comp_t^h(r,s)} = P_t^h(r,s,SEP,MSS)\begin{bmatrix} \frac{1}{\xi} + \left(\frac{1}{\zeta} - \frac{1}{\xi}\right) P_t^h(r \mid SEP) \\ + \left(1 - \frac{1}{\zeta}\right) P_t^h(r \mid MSS) - P_t^h(r) \end{bmatrix}$$

$$* \beta_3 \left(\frac{ListAttr_t^h(r) + ListAttr_t^h(s)}{2} \right) \theta \left(1 + Comp_t^h(r,s)\right)^{(\theta - 1)}$$

$$+ P_t^h(r,s,CMB,MSS)\begin{bmatrix} \frac{1}{\xi} + \left(\frac{1}{\zeta} - \frac{1}{\xi}\right) P_t^h(r \mid CMB) \\ + \left(1 - \frac{1}{\zeta}\right) P_t^h(r \mid MSS) - P_t^h(r) \end{bmatrix}$$

$$* \beta_3 \left(\frac{ListAttr_t^h(r) + ListAttr_t^h(s)}{2} \right) \psi \left(1 + Comp_t^h(r,s)\right)^{(\psi - 1)}$$

The probability that store *r* and *s* will be the consumer's chosen set, in either a separate or combined pattern, changes by:

$$\frac{\partial P_t^h(r,s,CMB,MSS)}{\partial U_t^h(r,s \mid CMB)} \frac{\partial U_t^h(r,s \mid CMB)}{\partial Comp_t^h(r,s)} + \frac{\partial P_t^h(r,s,SEP,MSS)}{\partial U_t^h(r,s \mid SEP)} \frac{\partial U_t^h(r,s \mid SEP)}{\partial Comp_t^h(r,s)}$$

$$= P_t^h(r,s,SEP,MSS) * \begin{bmatrix} \frac{1}{\xi}\left(1 - P_t^h(r,s \mid SEP)\right) + \frac{1}{\zeta} P_t^h(r,s \mid SEP)\left(1 - P_t^h(SEP \mid MSS)\right) \\ + \left(1 - P_t^h(MSS)\right) P_t^h(SEP \mid MSS) P_t^h(r,s \mid SEP) \end{bmatrix} *$$

$$\beta_3 \left(\frac{ListAttr_t^h(r) + ListAttr_t^h(s)}{2} \right) \theta \left(1 + Comp_t^h(r,s)\right)^{(\theta - 1)}$$

$$+ P_t^h(r,s,CMB,MSS) * \begin{bmatrix} \frac{1}{\xi}\left(1 - P_t^h(r,s \mid CMB)\right) + \frac{1}{\zeta} P_t^h(r,s \mid CMB)\left(1 - P_t^h(CMB \mid MSS)\right) \\ + \left(1 - P_t^h(MSS)\right) P_t^h(CMB \mid MSS) P_t^h(r,s \mid CMB) \end{bmatrix} *$$

$$\beta_3 \left(\frac{ListAttr_t^h(r) + ListAttr_t^h(s)}{2} \right) \psi \left(1 + Comp_t^h(r,s)\right)^{(\psi - 1)}$$

The expression shows that this change is always positive.

Taken together, we find that ceteris paribus, an increase in store complementarity between store *r* and *s* will enhance the MSS patronage of *r* (and, especially, its propensity to be chosen along with store *s*, in either a separate or combined pattern), but will reduce the probability that it is selected as a single store.

Impact of a change in store r's list attraction. The shopping list attraction intervenes in the single-store shopping utility, as well as in all MSS utilities involving store r. Hence, its total effect can be obtained as:

$$\frac{\partial P_t^h(r)}{\partial ListAttr_t^h(r)} = \frac{\partial P_t^h(r)}{\partial U_t^h(r)} \frac{\partial U_t^h(r)}{\partial ListAttr_t^h(r)} + \sum_{l, l \neq r} \frac{\partial P_t^h(r)}{\partial U_t^h(r,l \mid SEP)} \frac{\partial U_t^h(r,l \mid SEP)}{\partial ListAttr_t^h(r)}$$
$$+ \sum_{l, l \neq r} \frac{\partial P_t^h(r)}{\partial U_t^h(r,l \mid CMB)} \frac{\partial U_t^h(r,l \mid CMB)}{\partial ListAttr_t^h(r)}$$

Here, $\frac{\partial U_t^h(r)}{\partial ListAttr_t^h(r)} = \beta_3$, $\frac{\partial U_t^h(r,l \mid SEP)}{\partial ListAttr_t^h(r)} = \frac{\beta_3}{2}\left(1 + Comp_t^h(r,s)\right)^{\varphi}$, and

$\frac{\partial U_t^h(r,l \mid CMB)}{\partial ListAttr_t^h(r)} = \frac{\beta_3}{2}\left(1 + Comp_t^h(r,s)\right)^{\psi}$, and the other components can be obtained from [A.9b], [A.10e] and [A.11b] above, after replacing s by l. Note that the impact of a change in list attraction, even ceteris paribus (that is, even if that change in list attraction does not, in itself, affect complementarity), will depend on the store r's complementarity with other stores. Moreover, increasing the store's list attraction may enhance or reduce SSS at the store, depending on the net effect of the different components in the expression.

We further note that, if only SSS were considered, the effect would simplify to:

$$\frac{\partial P_t^h(r \mid SSS)}{\partial ListAttr_t^h(r)} = \frac{\beta_3}{\zeta} P_t^h(r \mid SSS)(1 - P_t^h(r \mid SSS))$$

– an expression that does not contain any complementarity component.

Impact of a change in store r's marketing mix within a product category. Based on the above, it is easy to see that a change in a marketing instrument $X_t(c,r)$ of store r within a specific category (e.g. a change in list price, assortment size or private label share), on the store's visit probability, is given by:

$$\frac{\partial P_t^h(r)}{\partial X_t(c,r)} = \frac{\partial P_t^h(r)}{\partial ListAttr_t^h(r)} \frac{\partial ListAttr_t^h(r)}{\partial X_t(c,r)} + \sum_{l, l \neq r} \frac{\partial P_t^h(r)}{\partial Comp_t^h(r,l)} \frac{\partial Comp_t^h(r,l)}{\partial X_t(c,r)}$$

Elasticities

The expressions above refer to marginal effects. Elasticity expressions are easily obtained by multiplying these marginal effects by the variable that is changed (i.e. inter-store distance, complementarity or list attraction), and dividing it by the probability of interest.

Appendix 4 Survey Items for the Measurement of Category Factors

To obtain the category factors “hedonic (versus functional) product”, “visibility of consumption” and “quality variability”, three experts rated each of the 48 categories in our dataset on each of these three characteristics. For this purpose, the following survey items were used:

Hedonic (versus functional) product. “How would you rate the nature of this product category? (1: definitely functional; 5: definitely hedonic)” (Leclerc, Schmitt and Dubé 1994)

Visibility of consumption. “The possession and usage of this product category is visible to people other than my immediate family or housemates. (1: strongly disagree; 5: strongly agree)” (DelVecchio 2001)

Quality variability. “In this product category, there are big differences in quality between the various brands. (1: strongly disagree; 5: strongly agree)” (Steenkamp et al. 2004)